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Essays on Asset Pricing using Information from Option Markets

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Declaration of Authorship

I, Konstantinos Gkionis, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

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Details of collaboration:

- Chapter 1 is co-authored with Prof. Alexandros Kostakis, Prof. George Skiadopoulos, and Przemyslaw S. Stilger. The sample of the risk-neutral moments has been provided by Przemyslaw S. Stilger. All other tasks related to data gathering, preparation as well as statistical analyses are solely my own work. The write-up and presentation of results have been carried out collectively with my co-authors.
- Chapter 2 is co-authored with Prof. Alexandros Kostakis and Prof. Konstantinos Stathopoulos. All tasks related to data gathering, preparation as well as statistical analyses are solely my own work. The write-up and presentation of results have been carried out collectively with my co-authors.
- Chapter 3 is co-authored with Prof. George Skiadopoulos. All tasks related to data gathering, preparation as well as statistical analyses are solely my own work. The write-up and presentation of results have been carried out collectively with my co-author.

Abstract

Chapter 1 examines whether the option market leads the stock market with respect to positive in addition to negative price discovery. We document that a long only portfolio containing the stocks with the highest values of risk-neutral skewness yields significant outperformance in the post ranking week during 1996 to 2014. This outperformance is driven by stocks that are relatively underpriced and exposed to greater downside risk. These findings are consistent with a trading mechanism, where investors may choose to exploit stock underpricing by buying (selling) OTM call (put) options, rather than directly buying the underlying stock, to avoid exposure to its downside risk.

Chapter 2 examines the effects of political uncertainty around US presidential elections on a firm's risk. We utilize information embedded in short term options and exploit cross sectional differences in firms' political features, such as their sensitivity to economic policy uncertainty, the firm's exposure to the presidential party, its geographical political alignment with the presidential party, and its political connectedness through campaign contributions. We document that sensitive, exposed, and aligned firms exhibit a substantially higher degree of option-implied price and tail risk, command a higher premium, and feature an increased dispersion of investor beliefs around the presidential election day.

Chapter 3 utilizes the context of affine general equilibrium models, where the vector of state variables is affine on the level of the term structure of the risk-neutral cumulants (RNCs) of the return distribution of a claim on aggregate consumption. We constructs factors of affine transformations of the term structure of the RNCs of the Standard and Poor's S&P 500 index, as proxies for the state vector. The pricing performance of the factors is found to be insignificant, even once single maturity RNCs are employed to construct factors. Factors are not priced within an ICAPM setting either.

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Chapter 1

Positive Stock Information In Out-Of-The-Money Option Prices

1.1 Introduction

In the real world of incomplete capital markets characterized by limits-to-arbitrage and information asymmetry, option payoffs cannot be perfectly replicated by the underlying assets, and hence options are not redundant assets as in the Black and Scholes (1973) paradigm (Ross (1976), Detemple and Selden (1991), and Back (1993)). An informed investor may choose to trade in the option market, if it is sufficiently liquid, to exploit the higher leverage embedded in options (Black (1975), Easley, O'Hara, and Srinivas (1998)), or to disguise her information signal in the presence of noise traders (An, Ang, Bali, and Cakici (2014)). As a consequence, option prices may convey information that is not already incorporated into the price of the underlying asset. In fact, there is a growing body of evidence that option-based variables can predict future stock returns.[1]

[1] Pan and Poteshman (2006) show that the put-to-call option volume ratio is inversely related to future stock returns. Hu (2014) finds that option-induced stock order imbalance is positively related to next-day stock returns. Johnson and So (2012) show that a high option-to-stock volume ratio predicts low stock performance. Similar is the conclusion of Ge, Lin, and Pearson (2016),

With respect to information extracted from option prices, Xing, Zhang, and Zhao (2010) find that stocks exhibiting the steepest implied volatility smirks subsequently underperform. Ofek, Richardson, and Whitelaw (2004) and Cremers and Weinbaum (2010) document that stocks which feature the most negative call-put implied volatility spreads, reflecting deviations from put-call parity due to relatively expensive puts, yield abnormally negative returns. An et al. (2014) find that stocks with large increases (decreases) in put (call) implied volatilities over the previous month are characterized by low future returns. Finally, Rehman and Vilkov (2012) and Stilger, Kostakis, and Poon (2017) find that a strongly negative Risk-Neutral Skewness (RNS) value, arising from very expensive out-of-the-money (OTM) puts relative to OTM calls, signals future stock underperformance (i.e. negative alpha).

In this chapter, we study the relation between RNS and future stock returns. Consistent with the above studies, we confirm the positive relation between RNS and future stock returns. We contribute to the literature by proposing and empirically validating a trading mechanism that explains why and under what conditions, a stock portfolio which contains the highest RNS stocks outperforms (i.e. it delivers a positive alpha). The mechanism is novel but it does not exclude other explanations, such as price pressure effects, or inside information. Furthermore, we examine how quickly the information embedded in high RNS stocks is subsequently incorporated into the underlying stock price.

According to the trading mechanism we conjecture, if the underlying stock is

who additionally document the ability of option volume associated with synthetic long positions to positively predict stock returns. Moreover, a number of studies have also examined the informational content of option-based variables in the context of: expected stock returns based on analyst price targets (Bali, Hu, and Murray, 2017), option returns (Goyal and Saretto (2009), Bali and Murray (2013), and Muravyev (2016)), equity risk (Chang, Christoffersen, Jacobs, and Vainberg (2012)), market timing and asset allocation strategies (Kostakis, Panigirtzoglou, and Skiadopoulos (2011), DeMiguel, Plyakha, Uppal, and Vilkov (2013), and Kempf, Korn, and Sassning (2015)), and corporate events such as earnings announcements and takeovers (Amin and Lee (1997), Cao, Chen, and Griffin (2005), Jin, Livnat, and Zhang (2012), Chan, Ge, and Lin (2015), Augustin, Brenner, and Subrahmanyam (2015)).

perceived to be underpriced, investors who anticipate a subsequent price correction may resort to the option market to buy (sell) OTM calls (puts) in order to lever up their positions and maximize their trading profits.[2] However, risk averse market makers may not be able to perfectly hedge their counterparty positions, e.g., due to asymmetric information, transaction costs, stock price jumps, and the downside or inventory risk they may face by buying the underlying stock. In this case, their supply curve of OTM options is not perfectly elastic, and hence they ask for a higher (lower) price to sell (buy) OTM calls (puts), leading to a higher RNS value. As a result, to the extent that market forces subsequently correct this underpricing, a relatively high RNS value or a large increase in RNS (ΔRNS) may signal future stock outperformance.

The signalled outperformance should be stronger, if the underlying stock exhibits substantial downside risk. In this case, investors would be more incentivized to buy OTM calls, rather than buying the stock itself, to lever up their long positions without being exposed to downside risk (see Back, 1993, and Pan and Poteshman, 2006, for related arguments). At the same time, risk averse market makers would require a higher premium to write these OTM calls because they would have to resort to the underlying market to hedge their option position, and hence they would also be exposed to the greater downside risk. In sum, a relatively high RNS or ΔRNS value should be even more informative with respect to the future outperformance of an underpriced, stock if its downside risk is more pronounced.

It is also expected that the RNS signal should be informative for stock outperformance, if options are sufficiently liquid in absolute terms or relatively to the underlying stock. Otherwise, if their bid-ask spreads are too large, the incentive to resort to the option market to speculate on stock underpricing becomes weaker because round-trip transaction costs could eliminate the anticipated trading profit.

[2] Bali and Murray (2013) provide examples of synthetic skewness assets, which yield a high payoff in the case of a *large* increase in the price of the underlying stock. The construction of these skewness assets involves buying (selling) OTM calls (puts).

In addition, if options are too thinly traded relative to the underlying stock, an informed investor may choose not to trade in the option market to avoid revealing her information.

The stock outperformance that a high RNS value may signal should be *short-lived* since RNS is computed from publicly available OTM option prices. This conjecture is also consistent with the notion of arbitrage asymmetry (see Stambaugh, Yu, and Yuan, 2015); stock underpricing should be rather quickly corrected by arbitrageurs without facing the constraints that apply in the case of stock overpricing.[3]

We empirically test the above conjectures. To this end, we use two rather diverse proxies for stock mispricing: the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2016), and the composite mispricing rank (MISP) of Stambaugh et al. (2015) and Stambaugh and Yuan (2017). We measure stock downside risk by using a direct as well as an indirect proxy. The direct proxy is the expected idiosyncratic skewness (EIS^P) of the underlying stock returns under the physical measure introduced by Boyer, Mitton, and Vorkink (2010). The indirect proxy is the estimated shorting fee (ESF) of Boehme, Danielsen, and Sorescu (2006).[4] In addition, we utilize the average relative bid-ask spread (RSPREAD) of the options used to calculate the RNS value to capture option liquidity in absolute terms and the average daily option-to-stock volume ratio (O/S) in the prior 12 months to proxy for the option liquidity relative to the underlying stock.

Our results corroborate the conjectured trading mechanism. First, we find that the long-only quintile portfolio of stocks with the highest RNS (ΔRNS) values

[3]Even though stock underpricing should be corrected quicker than stock overpricing due to the asymmetry of limits-to-arbitrage affecting long and short strategies, there are examples in the literature where stock underpricing is not corrected quickly. A very prominent example is the post earnings announcement drift (see Dubinsky, Johannes, Kaeck, and Seeger, 2018, and references therein).

[4]In line with the arguments and the evidence of Grullon, Michenaud, and Weston (2015), stock downside risk is expected to be greater in the absence of short selling constraints, i.e., when the shorting fee is low.

significantly outperforms, yielding a Fama-French-Carhart (FFC) alpha of 12 (10) basis points (bps) in the post-ranking week with a Newey-West (NW) t-stat of 3.11 (3.15). *A fortiori*, the intersection of the highest RNS and the highest ΔRNS quintiles yields an FFC alpha of 21 bps in the post-ranking week (NW t-stat: 4.03).

Second, we find that a relatively high RNS value becomes a strong signal for subsequent outperformance mainly for stocks that are also perceived to be underpriced and for stocks whose downside risk is more pronounced. In fact, we find that both stock underpricing and pronounced downside risk are reinforcing mechanisms of the RNS signal with respect to subsequent stock outperformance. Using triple-sorted portfolios, we find that a portfolio of stocks that exhibit higher than median RNS values, are relatively underpriced, and are exposed to greater downside risk yields a strongly significant FFC alpha of 22 bps *per week*.

Third, we find that the stock outperformance signalled by RNS is significant only when options are fairly liquid relative to the underlying stock and their bid-ask spreads are not too high. Fourth, we decompose the post-ranking weekly returns of the RNS- (ΔRNS-) sorted portfolios and find that most of this abnormal performance is earned on the first post-ranking day. We further decompose the first post-ranking daily returns into their overnight and intraday components and find that the signalled outperformance is entirely earned overnight.

Last but not least, we examine whether RNS simply captures stock price pressure. In that case, the positive relation of RNS with future stock returns could be a manifestation of a short-term reversal effect (see Goncalves-Pinto et al. (2016)). Alleviating this potential concern, we show that RNS exhibits an almost zero rank correlation with the same-day and 5-day cumulative stock return. Equally importantly, the positive RNS gradient with respect to post-ranking stock returns remains intact, even when we firstly condition upon positive, zero or negative stock returns on, or up to the portfolio sorting day.

Collectively, our results corroborate the arguments of Easley et al. (1998) and An et al. (2014) on cross-market predictability by showing that the expensiveness of OTM calls relative to OTM puts predicts future stock returns. Furthermore, our findings lend support to the demand-based option pricing framework of Garleanu, Pedersen, and Poteshman (2009) by showing that a relatively high RNS value may reflect excess demand for OTM calls from investors who attempt to exploit stock underpricing. In addition, our results comply with the mechanism of Hu (2014), according to which market makers translate option order imbalance into stock order imbalance in their attempt to hedge their counterparty positions. In our setting, this mechanism can explain why a relatively high RNS value, arising from excess demand (supply) for OTM calls (puts), can predict stock outperformance.

Our results can also be regarded as complementary to the evidence of Pan and Poteshman (2006) and Ge et al. (2016), who show that high buyer-initiated OTM call option trading volume predicts stock outperformance. Instead of utilizing proprietary signed option trading volume data across different levels of moneyness, the RNS signal we employ conveniently summarizes information embedded in publicly available OTM option prices. To the extent that option prices reflect the impact of informed trading volume, their informational content should be equivalent.

1.2 Methodology and Data

1.2.1 Risk-Neutral Skewness: Computation

We compute the Risk-Neutral Skewness (RNS) of the option-implied stock return distribution using the model-free methodology of Bakshi, Kapadia, and Madan (2003). Using the time t prices of OTM call $(C_t(\tau; K))$ and put $(P_t(\tau; K))$ options with strike price K and time-to-expiration τ, the $RNS(\tau)$ for stock i is defined as:

$$RNS_{i,t}(\tau) = \frac{\exp(r\tau)\left(W_t(\tau) - 3\mu_t(\tau) V_t(\tau)\right) + 2\mu_t^3(\tau)}{\left[\exp(r\tau) V_t(\tau) - \mu_t^2(\tau)\right]^{3/2}}, \tag{1.1}$$

where r is the risk-free rate, $\mu_t(\tau)$ is given by

$$\mu_t(\tau) = \exp(r\tau) - 1 - \frac{\exp(r\tau)}{2} V_t(\tau) - \frac{\exp(r\tau)}{6} W_t(\tau) - \frac{\exp(r\tau)}{24} X_t(\tau), \tag{1.2}$$

and $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$ are the time t prices of $\tau-$maturity quadratic, cubic, and quartic contracts, defined as contingent claims with payoffs equal to the second, third, and fourth power of stock i log return, respectively. The corresponding prices of these three contracts are given by

$$V_t(\tau) = \int_{S_t}^{\infty} \frac{2\left(1 - \log\left(\frac{K}{S_t}\right)\right)}{K^2} C_t(\tau; K)\, dK + \int_0^{S_t} \frac{2\left(1 + \log\left(\frac{S_t}{K}\right)\right)}{K^2} P_t(\tau; K)\, dK, \tag{1.3}$$

$$\begin{aligned} W_t(\tau) \;=\; & \int_{S_t}^{\infty} \frac{6\log\left(\frac{K}{S_t}\right) - 3\left(\log\left(\frac{K}{S_t}\right)\right)^2}{K^2} C_t(\tau; K)\, dK - \\ & - \int_0^{S_t} \frac{6\log\left(\frac{S_t}{K}\right) + 3\left(\log\left(\frac{S_t}{K}\right)\right)^2}{K^2} P_t(\tau; K)\, dK, \end{aligned} \tag{1.4}$$

and

$$
\begin{aligned}
X_t(\tau) &= \int_{S_t}^{\infty} \frac{12\left(\log\left(\frac{K}{S_t}\right)\right)^2 - 4\left(\log\left(\frac{K}{S_t}\right)\right)^3}{K^2} C_t(\tau; K) + \\
&+ \int_0^{S_t} \frac{12\left(\log\left(\frac{S_t}{K}\right)\right)^2 + 4\left(\log\left(\frac{S_t}{K}\right)\right)^3}{K^2} P_t(\tau; K)\, dK, \qquad (1.5)
\end{aligned}
$$

where S_t is the price of the underlying stock adjusted by the discounted value of future dividends.

To compute the integrals that appear in $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$, a continuum of OTM option prices would be required. However, traded equity options are available only at few and discrete strikes. In line with Rehman and Vilkov (2012), Conrad, Dittmar, and Ghysels (2013), and Stilger et al. (2017), we require at least two OTM puts and two OTM calls per stock with the same expiry date to compute RNS on a given day. We interpolate the implied volatilities of the available options, separately for puts and calls, between the lowest and the highest available moneyness using a piecewise Hermite polynomial, and we extrapolate beyond the lowest and the highest moneyness using the implied volatility at each boundary. This way, we fill in 997 grid points in the moneyness range from 1/3 to 3. We convert these implied volatilities to the corresponding option prices via the Black-Scholes formula. Finally, we use these option prices to determine $V_t(\tau)$, $W_t(\tau)$, and $X_t(\tau)$ by numerically computing the corresponding integrals via Simpson's rule.

We use daily prices of OTM equity options with 10 to 180 days-to-maturity. The closing option price is computed as the average of the bid and ask prices. We discard options with zero open interest, zero bid price, negative strike, price less than \$0.50, missing implied volatility, and non-standard settlement. As mentioned above, we also filter out stocks with less than two OTM puts and two OTM calls with the same expiry on a given day. Among the eligible sets of options that satisfy the above criteria, we use the one with the shortest maturity. This choice is consistent with the conjecture that investors who seek to profit from stock underpricing would trade short-dated options because, for a given level of moneyness, they offer considerably higher leverage relative to long-dated options.

1.2.2 Data Sources and Firm Characteristics

We obtain daily data on equity options from OptionMetrics IvyDB and on stocks from CRSP. Our stock universe consists of U.S. common stocks (share codes 10 and 11) listed on NYSE, NYSE MKT, and NASDAQ (exchange codes 1, 2, and 3). The sample period is January 1996 to June 2014. The risk-free rate is proxied by the 3-month T-Bill rate from the Federal Reserve H.15 release. Data on daily factor returns are sourced from Kenneth French's website. We also compute overnight and intraday equity factor returns in the spirit of Lou, Polk, and Skouras (2018).

We construct a series of firm-level variables, whose definitions are provided in the Appendix. In particular, we compute the distance between the actual stock price and the option-implied stock value (DOTS) as in Goncalves-Pinto et al. (2016), the Expected Idiosyncratic Skewness EIS^P of stock returns under the physical measure of Boyer et al. (2010), the Estimated Shorting Fee (ESF) of Boehme et al. (2006), stock return momentum (MOM), market capitalization (MV), and the book-to-market value ratio (B/M). We also use the composite stock mispricing rank (MISP) of Stambaugh et al. (2015) and Stambaugh and Yuan (2017), which is available from Robert Stambaugh's website. A low (high) value for DOTS and MISP indicates that the stock is relatively underpriced (overpriced). A low (high) value for EIS^P and ESF indicates that the stock entails greater (lower) downside risk. As a proxy for option liquidity, we compute the average relative bid-ask spread (RSPREAD) across the OTM options used to compute RNS on a given day. As a proxy for option liquidity relative to stock liquidity, we compute the average daily option-to-stock volume ratio (O/S) in the prior 12 months, using all available options expiring from 10 to 180 days.

1.2.3 Descriptive Statistics

Our sample of RNS values consists of 3,121,205 permno-day observations. Table 1.1 reports the descriptive statistics for the option dataset used to compute these daily RNS values. The average RNS value is -0.41 and the average maturity of the utilized OTM options is 91.8 days. The majority of these OTM options have sizeable open interest, they are not particularly deep-out-of-the-money, and they exhibit a median RSPREAD of 14.6%. Moreover, RNS values are available for a sufficiently large cross-section of stocks on a given day, with a median of 671 stocks.[5]

Next, we examine whether RNS is correlated with firm characteristics that are known to be related to future stock returns or with the stock characteristics we use in the subsequent portfolio analysis. To this end, Table 1.2 reports the pairwise Spearman's rank correlation coefficients between RNS and a series of variables; the corresponding Pearson correlation coefficients are very similar. Since our benchmark analysis relies on weekly portfolio sorts every Wednesday, the reported coefficients are the time-series averages of the rank correlation coefficients computed every Wednesday during our sample period.

The conclusion from Table 1.2 is that RNS is not highly correlated with any of the variables considered. The rank correlation of ΔRNS with these variables is even lower. As a result, stock portfolios constructed on the basis of RNS or ΔRNS do not simply mimic the performance of portfolios constructed on the basis of other stock characteristics. These low rank correlation coefficients also ensure

[5] In our benchmark analysis, each RNS-sorted quintile portfolio contains, on average, 133 stocks, whereas each ΔRNS quintile portfolio contains, on average, 125 stocks.

that bivariate or trivariate independently-sorted portfolios on the basis of RNS and other stock characteristics will be well populated.

Of particular interest is the rank correlation of RNS and ΔRNS with DOTS. Goncalves-Pinto et al. (2016) conjecture that DOTS could reflect both stock price pressure and informed trading embedded in option prices. However, they show that it mainly captures stock price pressure, rendering it a meaningful mispricing proxy at the daily frequency. We find that RNS and ΔRNS exhibit relatively low rank correlation with DOTS (average: -0.31). Hence, we claim that RNS does not mimic DOTS, and hence it cannot be regarded as a stock price pressure or mispricing proxy. Supporting further the latter argument, we find that RNS exhibits an even lower rank correlation with MISP, whereas the correlation of ΔRNS with MISP is zero. Finally, consistent with the argument that RNS does not reflect stock price pressure, its average rank correlation coefficient with the stock return on the portfolio sorting day (RET(1)) or the cumulative 5-day stock return (RET(5)) is close to zero.

1.3 RNS and ΔRNS Portfolio Sorts

The starting point of our analysis is to examine the relation between RNS and future stock returns at the weekly frequency. To this end, we sort stocks in ascending order according to their RNS (ΔRNS) values and assign them to quintile portfolios. For our benchmark results, we construct these portfolios using RNS values computed at market close every Wednesday. Arguably, the level of RNS could be inherently related to a series of firm characteristics (see Dennis and Mayhew, 2002, for an empirical investigation). However, the low degree of persistence of daily RNS values implies that RNS primarily reflects transient price pressure in OTM options.[6] Nevertheless, controlling for firm fixed effects and a potential option maturity effect, we also sort stocks into quintile portfolios on the basis of the change in their RNS value (ΔRNS) at market close every Wednesday relative to the previous trading day.

1.3.1 Portfolio Characteristics

Table 1.3 reports the average characteristics of the constituent stocks for each RNS- (Panel A) and ΔRNS-sorted (Panel B) quintile portfolio. We find that the stocks in the highest RNS quintile have smaller average capitalization relative to the stocks in the lowest RNS quintile.[7] Interestingly, the highest RNS quintile contains stocks that are, on average, characterized as relatively underpriced according to DOTS, but relatively overpriced according to MISP. The stocks in the highest RNS quintile also exhibit, on average, lower exposure to downside risk according to EIS^P and ESF, and their average return on the portfolio sorting day or during the prior five trading days is lower relative to the corresponding average return of the stocks in the lowest RNS quintile. However, it should be noted that, as illustrated by the low rank correlation coefficients between RNS and the rest of the variables reported in Table 1.2, a large cross-sectional variation within each quintile portfolio underlies these average values. We explore this variation using bivariate and trivariate portfolio sorts in the subsequent sections.

Regarding ΔRNS-sorted portfolios, the spread in the average values between the highest and the lowest quintiles mostly disappears for persistent firm characteristics (e.g., MV, B/M, MISP, EIS^P, ESF). This is an expected finding because ΔRNS cancels out firm fixed effects that potentially determine the level of RNS.

[6] The average AR(1) coefficient of daily RNS values across the firms in our sample is 0.70. In comparison, the corresponding average AR(1) coefficient of daily Risk-Neutral Variance values is much higher (0.96).

[7] RNS takes predominantly negative values. Hence, a relatively high RNS value is defined with respect to the cross-sectional distribution of RNS values on a given day, but it can still have a negative sign.

On the other hand, the corresponding spread in average values for the variables that capture transient information at the daily frequency (e.g., DOTS, RET(1), RET(5)) remains significant. Nevertheless, the low rank correlation coefficients reported in Table 1.2 ensure that ΔRNS portfolio sorts by no means coincide with stock mispricing or return-based portfolio sorts.

1.3.2 Post-Ranking Performance

Table 1.4 reports the weekly post-ranking performance of RNS-sorted (Panel A) and ΔRNS-sorted (Panel B) quintile portfolios. In particular, we compute weekly equally-weighted portfolio returns by compounding the corresponding daily portfolio returns from the sorting Wednesday market close until the following Wednesday market close. For both RNS- and ΔRNS-sorted quintiles, we find a monotonically positive gradient in the post-ranking premia as we move from the portfolio with the lowest RNS (ΔRNS) stocks to the portfolio with the highest RNS (ΔRNS) stocks. Most importantly for the focus of our study, we find that the quintile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a significant post-ranking weekly premium of 32 (29) bps.

Next, we examine the post-ranking performance of RNS- and ΔRNS-sorted quintiles on a risk-adjusted basis. We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FFC alpha of 12 (10) bps in the post-ranking week with a NW t-stat of 3.11 (3.15).[8,9] To highlight

[8]Throughout the study, we compute t-statistics using NW standard errors with the lag length (q) given by the automatic lag selection procedure of Newey and West (1994), where $q = 4(T/100)^{2/9}$ and T is the sample size. In our benchmark analysis, we utilize post-ranking portfolio returns for 962 weeks, hence $q = 7$.

[9]We present results for quintile portfolios to ensure that they contain a large number of stocks, and hence are well diversified throughout our sample period. The documented outperformance is even more significant when we instead consider decile portfolios. In particular, the decile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a highly significant FFC alpha of 19 (12) bps in the post-ranking week.

its economic significance, this outperformance corresponds to an annualized FFC alpha of 6.43% (5.33%).

We can draw four remarks based on the findings reported in Panels A and B of Table 1.4. First, our finding shows that a relatively high RNS (ΔRNS) value can be an informative signal for significant stock outperformance at the weekly frequency. Second, Table 1.4 shows that the spread between the highest and the lowest RNS (ΔRNS) quintiles yields an FFC alpha of 24 (25) bps in the post-ranking week, with a NW t-stat of 5.03 (6.65). This finding is consistent with the evidence of Rehman and Vilkov (2012) and Stilger et al. (2017) who show that, at the *monthly* frequency, the relation between RNS and future stock returns is positive. Third, contributing further to this strand of the literature, we show that this positive relation also holds when we alternatively use ΔRNS, which is well-suited to capture the transient nature of the information embedded in RNS. Fourth, we find that, at the weekly frequency, the significant abnormal performance of the long-short RNS (ΔRNS) strategy is symmetrically sourced from *both* the underperformance of the lowest RNS (ΔRNS) quintile *and* the outperformance of the highest RNS (ΔRNS) quintile.

Panel C of Table 1.4 reports the corresponding performance of two bivariate stock portfolios constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. In line with the argument that relatively high RNS and ΔRNS values can signal subsequent stock outperformance, we find that the portfolio of stocks with the highest RNS and the highest ΔRNS values yields a strongly significant FFC alpha of 21 bps in the post-ranking week (i.e., 11.53% p.a.). Moreover, confirming that RNS and ΔRNS are positively related to future stock returns, the spread between the portfolio with the highest RNS & ΔRNS values and the portfolio with lowest RNS & ΔRNS values yields an FFC alpha of 40 bps in the post-ranking week (NW t-stat: 5.80).

1.3.3 Robustness Checks

We conduct a series of tests to examine the robustness of our benchmark results to alternative methodological choices. First, we risk-adjust the post-ranking performance of RNS- and ΔRNS-sorted portfolios using the 5-factor Fama and French (2015) asset pricing model. Second, we sort stocks into quintile portfolios using the corresponding RNS and ΔRNS values computed at market close every Friday (rather than every Wednesday), and we estimate their weekly post-ranking performance by compounding daily portfolio returns until the following Friday market close. Third, we construct quintile portfolios by excluding from the sample stocks whose RNS values are computed from OTM option prices associated with zero total trading volume. Forth, we repeat our benchmark analysis in the considerably smaller cross-section of stocks whose RNS horizon is less or equal to roughly three months (94 days).

The corresponding results are presented in the Appendix and they confirm the conclusions of our benchmark analysis. The stock outperformance signalled by relatively high RNS and ΔRNS values becomes stronger and more significant when we use the 5-factor alpha as an alternative metric of risk-adjusted performance. Moreover, the magnitude and the significance of the documented stock outperformance remains intact when we instead use Friday portfolio sorts. In addition, in the case where we consider RNS values computed only from OTM options with positive total trading volume, the quintile portfolio containing the highest RNS stocks yields a similarly strong FFC alpha in the post-ranking week. Finally, even when we effectively exclude half of the stocks of our initial sample whose RNS horizon is greater than 94 days, we find a quantitatively similar outperformance that remains statistically significant at the five percent significance level.

In the Appendix, we also consider an alternative, “non-parametric” proxy for RNS (NPRNS), which directly measures the relative expensiveness between OTM calls and OTM puts. Following Bali et al. (2017), NPRNS is computed as the difference between the 30-day implied volatilities of OTM calls (deltas $= 0.20$ and 0.25) and OTM puts (deltas $= -0.20$ and -0.25). We compute NPRNS for the stocks in our benchmark analysis, and we construct NPRNS-sorted quintile portfolios at market close every Wednesday. Consistent with our benchmark results, we find that the quintile portfolio which contains the stocks with the highest NPRNS values yields a significant FFC alpha in the post-ranking week.

Throughout the chapter, we report the results obtained from the equally weighted portfolios rather the value weighted portfolios as the former is indicative for the average stock, whereas the latter is mainly representative for a small number of stocks with the greatest market capitalisation in the portfolio. To alleviate the potential concern that this choice drives our results, we repeat our benchmark analysis by forming value weighted portfolios. The results are reported in the Appendix and they are qualitatively identical. In particular, we find that the outperformance of the portfolio containing the stocks with the highest RNS values equals 13 bps (t-stat $= 3.68$).

We have also examined the performance of RNS- and ΔRNS-sorted portfolios using daily rebalancing. The corresponding results are reported in the Appendix, showing that the quintile portfolio containing the stocks with the highest RNS (ΔRNS) values yields a highly significant FFC alpha of 10 (9) bps on the *post-ranking day*. These results indicate that the largest part of the weekly stock outperformance documented in our benchmark analysis is earned on the first post-ranking day. A potential implication of this finding is that the information embedded in high RNS is subsequently quickly incorporated into the underlying stock price. Section 1.6 examines this issue in detail.

Last, we have also entertained the possibility that the documented outperformance signalled by high RNS and ΔRNS values may be driven by positive stock information embedded in OTM option prices around earnings announcements. To this end, we repeat our benchmark portfolio analysis excluding RNS observations ± 7 days around earnings announcement dates, which are sourced from Compustat. In unreported results, which are readily available upon request, we find that the outperformance of the highest RNS (ΔRNS) portfolio remains virtually identical to the one in our benchmark analysis. Hence, the stock information that is systematically embedded in relatively high RNS (ΔRNS) values cannot be attributed to an earnings announcement effect.

1.4 Why can high RNS Signal Stock Outperformance?

The robust stock outperformance signalled by relatively high RNS and ΔRNS values warrants further analysis to reveal its sources. To this end, we develop and test a trading mechanism that can give rise to this relation. We argue that a relatively high RNS value may reflect price pressure in OTM options, arising from the trading activity of speculators who resort to the option market to hold leveraged long positions on relatively underpriced stocks. To trade on their optimistic beliefs or positive information and maximize their leverage, investors would buy (sell) OTM call (put) options. The purchase of OTM calls is particularly attractive in comparison to directly purchasing the underlying stock because the former entail no exposure to the potential downside risk that holding the stock involves.

If risk averse market makers cannot perfectly hedge their counterparty positions, then consistent with the demand-based option pricing framework of Garleanu et al. (2009), this trading activity may exercise upward (downward) price pressure on OTM calls (puts). In fact, to hedge their positions, market makers would need to buy the underlying stock, and get exposed to downside and/or inventory risk. As a result, they would require a risk premium to act as counterparties, which is reflected in higher (lower) prices for selling (buying) OTM calls (puts) to the speculators. This mechanism renders OTM calls (puts) relatively more (less) expensive, resulting into a higher RNS value. In turn, a relatively high RNS value is followed by stock outperformance if market participants perceive this option trading activity as an informative signal and subsequently correct the stock underpricing, or if market makers, in their attempt to hedge their positions, translate this option order imbalance into stock order imbalance by buying the stock, and hence raise its price (Hu (2014)).

1.4.1 The Role of Stock Underpricing

A testable prediction implied by this mechanism is that a relatively high RNS value should be a strong signal for subsequent stock outperformance, primarily for those stocks that are perceived to be underpriced. Otherwise, there would be no incentive in the first place for investors to resort to the option market to set up synthetic long positions using OTM options.

To test this prediction, we construct double-sorted portfolios on the basis of RNS and a proxy for stock mispricing. For robustness, we use two alternative proxies for stock mispricing: *i*) the daily DOTS measure of Goncalves-Pinto et al. (2016), and *ii*) the monthly MISP rank of Stambaugh et al. (2015). These two proxies reflect rather diverse sources of information and they capture potential stock mispricing at different frequencies. In fact, they exhibit almost zero rank correlation. To begin with, we construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their RNS values at market close every Wednesday, and then, within each RNS tercile, we further sort stocks into terciles according to their mispricing proxy values.

Panel A.1 of Table 1.5 reports the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when DOTS is used as a mispricing proxy. Consistent with the conjectured trading mechanism, we find that the outperformance of the stocks with the highest RNS values is mainly driven by those stocks that are perceived to be the most underpriced. The tercile portfolio with the most underpriced stocks within the highest RNS tercile yields an impressive FFC alpha of 29 bps (NW t-stat: 5.98) in the post-ranking week. To the contrary, the tercile portfolio with the most overpriced stocks within the highest RNS tercile actually yields a significant negative FFC alpha. In fact, the spread between the most underpriced and the most overpriced stocks within the highest RNS tercile yields a strongly significant FFC alpha of 43 bps in the post-ranking week. The conclusion from these results is that a relatively high RNS value per se is not a sufficient condition for subsequent stock outperformance, and hence it cannot be regarded itself as a proxy for stock underpricing.

-Table 5 here-

Panel B.1 of Table 1.5 reports the corresponding results when MISP is used as a mispricing proxy. We find that the tercile portfolio with the most underpriced stocks within the highest RNS tercile yields strong outperformance, whereas the corresponding portfolio with the most overpriced stocks yields an almost zero FFC alpha. Hence, these results confirm that a relatively high RNS value carries information regarding future stock outperformance if the stock is perceived to be underpriced in the first place, whereas it is uninformative if the stock is overpriced.

To further examine the interaction between RNS and stock underpricing, we alternatively construct independent double-sorted portfolios. Panels A.2 and B.2 of Table 1.5 report the weekly post-ranking performance of these portfolios for the DOTS and MISP mispricing proxies, respectively. The independent double-sorted portfolios are well populated. This reflects the low rank correlation coefficients between RNS and DOTS or MISP reported in Table 1.2 and alleviates the potential concern that a high (low) RNS value may coincide with a low (high) DOTS or MISP value.

The reported results support the argument that the combination of relatively high RNS and stock underpricing strengthens subsequent stock outperformance. Panel A.2 shows that the intersection of the stocks with the highest RNS and lowest DOTS values yields an FFC alpha of 23 bps (NW t-stat: 5.85) in the post-ranking week. To the contrary, the portfolio of stocks with the highest RNS and highest DOTS values yields a highly significant negative FFC alpha. Equally importantly, we find that the portfolio which combines the most underpriced stocks and the stocks with the lowest RNS values fails to deliver a significant FFC alpha. Hence, stock underpricing, as proxied by DOTS, becomes a strong signal for subsequent stock outperformance only when it is associated with a relatively high RNS value, confirming that investors have resorted to the option market to exploit it. In fact, the spread between the portfolio containing the lowest DOTS and highest RNS stocks and the portfolio containing the lowest DOTS and lowest RNS stocks yields a highly significant FFC alpha.[10] Finally, the corresponding results in Panel B.2 further support the argument that a relatively high RNS value ceases to be an informative signal regarding future outperformance for those stocks that are considered to be overpriced. These results also show that a low MISP value cannot be regarded either as a sufficient condition for subsequent stock outperformance; it becomes a valid signal when it is combined with a relatively high RNS value.

[10]The combination of stock mispricing and RNS is also informative with respect to subsequent stock underperformance. In particular, the portfolio of stocks with the highest DOTS (MISP) and lowest RNS values yields an FFC alpha of -23 (-26) bps in the post-ranking week. Consistent with the arguments of Stilger et al. (2017), this finding shows that the relation they have documented also holds with alternative mispricing proxies, and it becomes stronger at the weekly frequency. Moreover, the combination of stock mispricing and RNS becomes even more impressive in the context of an enhanced investment strategy. For example, a spread strategy that goes long the portfolio with the lowest DOTS & highest RNS stocks and goes short the portfolio with the highest DOTS & lowest RNS stocks would yield an FFC alpha of 46 bps per week.

1.4.2 The Role of Stock Downside Risk

The trading mechanism described above also yields a testable prediction regarding the role of stock downside risk. A relatively high RNS value is expected to be more informative with respect to the future outperformance of a stock if the latter entails greater downside risk. In this case, speculators have a stronger incentive to resort to the option market to trade on their optimistic beliefs by purchasing OTM calls rather than directly buying the stock. The RNS signal should also be more informative in this case because market makers would require an even higher risk premium to act as counterparties, and hence the option trading activity of speculators should be more clearly reflected in a higher RNS value.

To test this prediction, we construct double-sorted portfolios on the basis of RNS and a proxy for stock downside risk. For robustness, we use a direct as well as an indirect proxy. The direct proxy is the expected idiosyncratic skewness (EIS^P) of stock returns, introduced by Boyer et al. (2010). A relatively low EIS^P value indicates a higher probability of a large negative stock return in the future. The indirect proxy is the estimated shorting fee (ESF) of Boehme et al. (2006). A lower ESF value indicates looser short selling constraints, implying a higher probability of incurring substantially negative stock returns (see Grullon et al. (2015)).

We initially construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their RNS values at market close every Wednesday, and then, within each RNS tercile, we sort stocks into terciles according to their downside risk proxy values. Panels A.1 and B.1 of Table 1.6 report the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when EIS^P and ESF are used as a downside risk proxy, respectively.

In line with the prediction of the conjectured trading mechanism, we find that the outperformance signalled by a relatively high RNS value is mainly driven by those stocks that exhibit the most pronounced downside risk. In fact, within the highest

RNS tercile, the portfolio of stocks that are the most exposed to downside risk according to EIS^P (ESF) yields a significant FFC alpha of 17 (11) bps in the post-ranking week. To the contrary, within the highest RNS tercile, the portfolio of stocks characterized by the lowest exposure to downside risk does not subsequently outperform. As a result, when stock downside risk is limited, speculators are less incentivized to resort to the option market, and hence a relatively high RNS value does not carry information regarding future stock outperformance.

We also construct independent double-sorted portfolios on the basis of RNS and each of the downside risk proxies. This alternative approach ensures that the classification of stocks' downside risk exposure is made relative to the entire cross-section, not just within each RNS tercile. Panel A.2 (B.2) of Table 6 reports the post-ranking performance of these independent double-sorted portfolios when EIS^P (ESF) is used as a downside risk proxy.

The conclusions derived from the independent double-sorted portfolios are very similar to the ones derived from the conditional portfolio sorting approach. Regardless of the employed proxy, we confirm that it is the intersection of stocks that exhibit the highest RNS values and are the most exposed to downside risk which yields the strongest subsequent outperformance. To the contrary, the intersection of stocks with the highest RNS values and the least pronounced downside risk does not subsequently outperform. Stressing further the important role of downside risk, the spread between these two intersections yields a significant FFC alpha.[11] Concluding, these results further support the proposed trading mechanism, showing that a relatively high RNS value is an informative signal for significant

[11] The results in Table 1.6 also allow us to examine whether the reported stock outperformance is simply driven by a downside risk premium. Rejecting this claim, we find that downside risk alone is not a sufficient condition for subsequent stock outperformance. In fact, the combination of stocks that are the most exposed to downside risk but exhibit the lowest RNS values yields an FFC alpha close to zero. Moreover, within each downside risk classification, we find a positive relation between RNS and post-ranking portfolio performance.

outperformance primarily for those stocks that are the most exposed to downside risk.

1.4.3 Stock Underpricing and Downside Risk

In the previous sections, we examined *separately* the role of underpricing and the role of downside risk in explaining the ability of a relatively high RNS value to signal future stock outperformance. However, the ultimate testable prediction of the conjectured trading mechanism is that the *joint* presence of underpricing and pronounced downside risk should further reinforce the ability of a relatively high RNS value to predict stock outperformance.

We test this prediction by constructing independent triple-sorted portfolios. At market close every Wednesday, we independently sort stocks on the basis of their: *i*) RNS value, *ii*) mispricing proxy value, and *iii*) downside risk proxy value, and classify them as high or low relative to the corresponding median value. The intersection of these three independent classifications yields 8 portfolios for each of the four possible combinations of the mispricing and downside risk proxies. Table 1.7 reports the weekly post-ranking risk-adjusted performance of these portfolios.

The reported results confirm the validity of the proposed trading mechanism. In particular, we find that the intersection of stocks that exhibit relatively higher RNS values, are relatively underpriced, and are more exposed to downside risk (i.e., portfolio P5) yields the strongest outperformance in the post-ranking week. This pattern is robust for all mispricing and downside risk proxies. For example, the long-only portfolio of stocks with higher than median RNS values, lower than median DOTS values, and lower than median EIS^P values yields an FFC alpha of 22 bps per week (NW t-stat: 4.92), which corresponds to an annualized FFC alpha of 12.11%. This is a striking result, if one takes into account how broad the adopted classification scheme is.[12]

It should be also noted that we find robust and significant stock outperformance only when *all* of the three conditions implied by this mechanism are satisfied (high RNS, underpricing, and pronounced downside risk). Otherwise, in the case where even one of these conditions is not met, stock outperformance becomes either insignificant or not robust to the choice of the mispricing and downside risk proxies (see e.g., P1, P6, and P7).[13]

1.5 Option Liquidity

Our analysis suggests that speculators may resort to the option market to trade on their optimistic beliefs or positive information regarding a relatively underpriced stock. In line with Easley et al. (1998), their incentive to create synthetic long positions using options should be strong only if the latter are sufficiently liquid in absolute terms or relative to the underlying stock. Otherwise, if their bid-ask spreads are too large, then round-trip transaction costs could eliminate the anticipated trading profit. In addition, if options are too thinly traded relative to the underlying stock, an informed investor may choose not to trade in the option market to avoid revealing her information. Therefore, we expect that a

[12] In selecting a classification scheme for triple-sorted portfolios, we face the following tradeoff. On the one hand, a finer classification scheme can reveal the sources of stock outperformance in a sharper way. On the other hand, it may lead to sparsely populated portfolios, and hence the reported performance may be driven by a small number of stocks. The presented classification scheme is rather broad, ensuring that the triple-sorted portfolios are well populated. However, we have also examined alternative classification schemes, such as independently sorting stocks into terciles. In line with our arguments, this finer classification scheme yields an even stronger outperformance for the intersection of stocks that exhibit the highest RNS values, are the most underpriced, and are the most exposed to downside risk. Results are available upon request.

[13] We have repeated the analysis described in Section 1.4 by using ΔRNS instead of RNS. The conclusions from this approach are similar to the ones discussed here. A high ΔRNS value is a strong signal for future outperformance for those stocks that are perceived to be underpriced and more exposed to downside risk. We report the corresponding results in the Appendix.

relatively high RNS value would be more informative with respect to subsequent stock outperformance when it is computed from sufficiently liquid options.[14]

To test this hypothesis, we construct double-sorted portfolios on the basis of RNS and a proxy for option liquidity. As a proxy for option liquidity in absolute terms, we employ the average relative bid-ask spread (RSPREAD) of the OTM options used to compute the RNS value. As a proxy for option liquidity relative to the underlying stock liquidity, we use the average daily option-to-stock volume ratio (O/S) in the prior 12 months. A very high value of RSPREAD indicates that the utilized OTM options are highly illiquid. A very low value of O/S indicates that options are thinly traded relative to the underlying stock.

We initially construct bivariate conditional portfolios, where we firstly sort stocks into quintiles on the basis of their RNS values at market close every Wednesday, and then, within each RNS quintile, we further classify stocks into two categories (High versus Low) according to their option liquidity proxy values. To isolate the effect of highly illiquid options, we classify as high RSPREAD the values that are above the 80th percentile of the corresponding distribution within each RNS quintile. Similarly, we classify as low O/S the values that are below the 20th percentile of the corresponding distribution. Panel A.1 (B.1) of Table 1.8 reports the weekly post-ranking FFC alphas of selected equally-weighted portfolios when RSPREAD (O/S) is used as a liquidity proxy.

For both proxies, we find that, within the highest RNS quintile, the portfolio of stocks with the highly illiquid options yields an insignificant FFC alpha that is close to zero. To the contrary, within the highest RNS quintile, the portfolio of stocks with the sufficiently liquid options yields a highly significant FFC alpha in the post-ranking week. Hence, in line with the previous arguments, a relatively high

[14] The bid-ask spread is a very rough measure of the actual trading cost an investor faces in the option market. Muravyev and Pearson (2020) show that the real trading costs in option markets may be substantially lower than what the bid-ask spreads suggest. An empirical investigation of the actual round-trip trading cost an investor faces could be an interesting avenue for future research. We would like to thank Andreas Kaeck for pointing this out.

RNS value is informative with respect to subsequent stock outperformance only when options are sufficiently liquid in absolute terms or relative to the underlying stock.

For robustness, we alternatively construct independent double-sorted portfolios. This ensures that our classification of stocks into high or low RSPREAD (O/S) is done with respect to the entire cross-sectional distribution of RSPREAD (O/S) values on the corresponding day. Panel A.2 (B.2) of Table 1.8 presents the post-ranking FFC alphas of these portfolios when RSPREAD (O/S) is used as a proxy. We reach very similar conclusions to the ones derived from the conditional portfolio sorting approach. For either liquidity proxy, the intersection of the stocks with the highest RNS values and highly illiquid options yields an insignificant FFC alpha, whereas the intersection of the stocks with the highest RNS values and sufficiently liquid options yields strong subsequent outperformance.

1.6 Speed of Price Correction

The results in Section 1.3 convincingly show that a long-only portfolio of stocks with relatively high RNS or ΔRNS values subsequently yields significant outperformance. Since RNS is computed from publicly available option prices and long-only strategies face negligible limits-to-arbitrage, this robust pattern seems to be at odds with market efficiency. Motivated by this evidence, in this Section we examine how fast the information embedded in RNS is subsequently incorporated into the underlying stock prices.

1.6.1 Decomposing Weekly Returns

First, we decompose the weekly performance of RNS- and ΔRNS-sorted portfolios into their performance: *i*) on the first post-ranking trading day, and *ii*) during the rest of the post-ranking week, skipping the first post-ranking trading day. Panel A (Panel B) of Table 1.9 reports the results of this decomposition for the RNS- (ΔRNS-) sorted portfolios.

We find that most of the abnormal weekly return signalled by RNS is earned on the first post-ranking day. This is consistent with the conjecture that this stock outperformance should be rather short-lived. In particular, the highest RNS and ΔRNS quintiles yield a highly significant FFC alpha of 9 bps on the first post-ranking day. On the other hand, skipping the first post-ranking day, the quintile portfolio which contains the stocks with the highest RNS (ΔRNS) values yields an insignificant FFC alpha of only 3 (1) bps during the rest of the post-ranking week.

These results reveal that stock market participants quickly incorporate the informational content of a relatively high RNS (ΔRNS) value into the underlying stock price. Another important conclusion is that a relatively high RNS (ΔRNS) value contains genuine positive information about the underlying stock, since the stock outperformance earned on the first post-ranking day is not reversed in the following days. Had it subsequently reversed, the outperformance on the first post-ranking day could have simply been a manifestation of uninformative short-term price pressure in the option market, transmitted to the stock market by market makers hedging their positions.

In addition, this performance decomposition shows that the negative information embedded in the lowest RNS (ΔRNS) values is incorporated in the underlying stock prices at a slower pace. In fact, even if we skip the first post-ranking day, the quintile portfolio containing the stocks with the lowest RNS (ΔRNS) values yields a significant negative FFC alpha of -7 (-8) bps during the rest of the post-ranking week. This finding is consistent with the argument that the negative information embedded in option prices may be slowly diffused to the underlying stock price due to limits-to-arbitrage, such as short-selling constraints.

Equally importantly, even if we skip the first post-ranking day, a long-short RNS- (ΔRNS-) based spread strategy would yield a significant FFC alpha of 10 (9) bps during the rest of the post-ranking week. This finding confirms that the positive relation between RNS and future stock returns is neither driven by next-day return reversals nor can be explained by a potential non-synchroneity bias.

1.6.2 Overnight versus Intraday Returns

We further decompose the performance of RNS- and ΔRNS-sorted portfolios earned on the first post-ranking day into its overnight and intraday components. To this end, we follow Lou et al. (2018) in computing intraday and overnight stock returns. In particular, the intraday return for stock i on day d is defined as:

$$r^i_{intraday,d} = \frac{P^i_{close,d}}{P^i_{open,d}} - 1, \tag{1.6}$$

where $P^i_{open,d}$ ($P^i_{close,d}$) is the open (close) stock price on day d, and the overnight return for stock i on day d is defined as:

$$r^i_{overnight,d} = \frac{1 + r^i_{close-to-close,d}}{1 + r^i_{intraday,d}} - 1, \tag{1.7}$$

where $r^i_{close-to-close,d}$ is the standard daily close-to-close return. To estimate FFC alphas, we also construct the intraday and overnight versions of the corresponding factor returns. The risk-free rate is assumed to accrue overnight. Panel A of Table 1.9 reports the overnight versus the intraday performance decomposition for RNS-sorted portfolios, whereas Panel B reports the corresponding decomposition for ΔRNS-sorted portfolios.

We find that the stock outperformance predicted by relatively high RNS or ΔRNS values is entirely earned overnight. The highest RNS (ΔRNS) quintile yields an overnight FFC alpha of 13 (10) bps with a NW t-stat of 9.69 (8.30). This result further supports the argument that market participants very quickly incorporate the information embedded in publicly observable OTM option prices into the underlying stock price. Moreover, we confirm that relatively high RNS (ΔRNS) values carry genuinely positive information about the underlying stock since little of the overnight outperformance is subsequently reversed intraday.

Taken together, the results in this Section indicate a very fast price discovery process and point towards a relatively efficient market mechanism. The ability of relatively high RNS (ΔRNS) values to predict overnight stock outperformance can be further reconciled with market efficiency, if one takes into account the criticism of Battalio and Schultz (2006). Even though the potential non-synchroneity bias is negligible in our sample period, it is not entirely certain whether the computed RNS values could be practically used in real time to exploit the documented stock outperformance. Nevertheless, these results collectively show that the option market can lead the stock market with respect to positive price discovery too.

A remark is in order at this point. Unlike index options, the CBOE equity option market closes virtually simultaneously with the underlying stock market at 4pm (EST). Moreover, since March 5, 2008, OptionMetrics reports the best (or highest) 3:59pm (EST) bid and offer prices across all exchanges on which the option trades. It is unlikely that the systematic risk adjusted return we find is caused by a non-synchronicity issue. However, to alleviate any potential concerns, we repeat in the Appendix the decomposition of the first post-ranking day return for two subperiods. The first period ranges from January 1996 to February 2008, and the second period ranges from April 2008 to June 2014. We find that the overnight outperformance of the portfolio containing the stocks with the highest RNS values remains highly statistically significant in the second period with a FFC alpha equal to 5 bps (t-stat = 4.01).

1.7 Stock Price Pressure and Return Reversals

Our results indicate that the predictive ability of RNS over future stock returns derives from informed trading in OTM options, and that the option market leads the stock market with respect to price discovery. This interpretation is in line with the arguments of prior studies in the literature (see, *inter alia*, Pan and Poteshman (2006), Cremers and Weinbaum (2010), Xing et al. (2010), and An et al. (2014)). To the contrary, the recent study of Goncalves-Pinto et al. (2016) argues that the predictive ability of option-implied measures primarily reflects short-run return reversals following stock price pressure, rather than informed trading in the option market. Contributing to this debate, in this Section we examine whether RNS reflects stock price pressure, and whether its positive relation with future stock returns is simply a manifestation of the well-documented reversal effect of Lehmann (1990) and Jegadeesh (1990).[15]

First, we have documented that the pairwise rank correlation coefficient between RNS and the same-day stock return (RET(1)) or the cumulative 5-day stock return (RET(5)) is close to zero (see Table 1.2). Therefore, we argue that short-term stock depreciation (appreciation) is not mechanically associated with a higher (lower) RNS value, and hence RNS cannot be regarded as a proxy for stock price pressure.

Second, we examine whether the positive relation between RNS and future stock returns is exclusively driven from stocks that have recently experienced price pressure. To this end, we construct bivariate conditional portfolios, where we firstly sort stocks into terciles on the basis of their 1-, 3-, and 5-day cumulative stock returns, respectively, and then, within each return tercile, we further sort stocks into quintiles on the basis of their RNS values. Table 1.11 reports the weekly post-ranking performance of the corresponding portfolios. Interestingly, we find that the positive relation between RNS and post-ranking alphas is evident within

[15] For recent evidence, see also Avramov, Chordia, and Goyal (2006) and Nagel (2012).

each return tercile, and it is robust regardless of the window used to compute these returns. In fact, within the medium return tercile, where the average 1-, 3-, and 5-day cumulative stock return up to the portfolio sorting day is approximately zero, and hence no price pressure has been experienced, the spread between the highest and the lowest RNS quintiles yields a highly significant FFC alpha of 15, 16, and 19 bps, respectively, in the post-ranking week.

Last, we also find that, within the lowest return tercile, it is the stocks with the highest RNS values that subsequently yield the strongest outperformance. This result is consistent with our trading mechanism because the stocks in the lowest return tercile are more likely to be relatively underpriced due to downward price pressure, and a high RNS value reflects trading activity in the option market to exploit this underpricing. To the contrary, within the lowest return tercile, the stocks with the lowest RNS values subsequently underperform. Hence, we conclude that downward price pressure is not a sufficient condition for subsequent stock outperformance. It is followed by stock outperformance only when it is associated with a relatively high RNS value. We derive similar conclusions when we repeat the analysis of this section using ΔRNS instead of RNS as a criterion to sort stocks into portfolios. The corresponding results are reported in the Appendix.

1.8 Trading activity on OTM options

The main conjecture of our study is that a relatively high RNS predicts subsequent stock outperformance due to investors' trading activity on the stock's options market. The trading mechanism and the results we have presented in the previous sections are consistent with this hypothesis. In this Section, we directly test it. In particular, we construct a measure that captures the trading activity on OTM call options relative to OTM put options from investors opening new long positions. We find that the outperformance signalled by a relatively high RNS is not evident across all stocks. It exists only for the stocks where investors have bought predominantly, almost exclusively, OTM calls on their options market.

To construct a measure that captures the trading activity on OTM options we employ the International Securities Exchange (ISE) Open / Close Trade profile database. In contrast to the total traded volumes provided for each option contract by OptionMetrics (OM), the ISE dataset disaggregates the traded volume into the following categories. Traded volume from (i) buy orders that open new positions (open buy), (ii) buy orders that close existing written positions (close buy), (iii) sell orders that open new written positions (open sell), and (iv) sell orders that close existing purchased positions (close sell). Furthermore, ISE reports whether a market-maker (designated as a firm) or an investor (designated as a customer or professional customer) executed the trade. We construct OBC/T as the ratio of the trading volume due to investors' open buy trades on OTM calls to the trading volume due to investors' open buy trades on both OTM call and put options. OBC/T ranges from 0% to 100%. On a given trading day and for a given stock, it equals 0% (100%) if investors only executed trades to open new positions on OTM put (call) options. If investors did not execute any open buy orders on OTM call or put option contracts, the ratio is not available. The sample of stocks that have available both RNS and OBC/T values ranges from May 2005 to June 2014, containing, on average, 405 individual stocks per day. We follow Ge et al. (2016) and exclude the last quarter of 2008 from our sample that includes the short-sale ban during the financial crises and could potentially distort the results.

To assess the interaction between RNS, OBC/T, and subsequent stock performance, we construct independent double-sorted portfolios on the basis of RNS and OBC/T. In particular, we sort stocks every Wednesday, at market close, to three portfolios according to their OBC/T values: i) Low, if the OBC/T value is below the 40th percentile, ii) Medium, if the OBC/T value is between the 40th and 60th percentiles, and iii) High, if the OBC/T value is above the 60th percentile of the corresponding cross-sectional distribution. We chose the 40th and 60th percentiles as breaking points as they can uniquely classify stocks to three well-populated portfolios for every cross-sectional distribution in the sample. Furthermore, we also sort stocks in ascending order according to their RNS values and assign them to tercile portfolios. Finally, we construct the double-sorted portfolios as the intersections of the portfolios formed during the aforementioned independent univariate sorts.

Panel A of Table 1.12 reports the weekly post-ranking performance of the lowest and highest univariate OBC/T-sorted portfolios. Panel B reports the weekly post-ranking performance of the independent double-sorted RNS-OBC/T portfolios involving the highest and lowest RNS and OBC/T portfolios. We find that there is a strong cross-sectional relationship between OBC/T and subsequent stock outperformance, as the spread portfolio produces a highly statistically significant FFC alpha equal to 13 bps (t-stat: 3.85). Furthermore, Portfolio OBC/T-1 that contains the stocks whose open buy trading volume on OTM options is mainly due to trades on OTM puts, 16% on puts versus 84% on calls, on average, produces a negative alpha equal to -0.05 which, is though, statistically indistinguishable to zero. Portfolio OBC/T-3 that contains the stocks were the traded volume is virtually exclusively due to trades on OTM call options, 97% of the volume, on average, produces a subsequent statistically significant outperformance equal to 8 bps with a t-stat of 2.17.

The performance of the bivariate independent-sorted portfolios confirms the hypothesis of the study. It shows that investors' trading activity on OTM options drives the outperformance signalled by RNS. In particular, among the stocks with a relatively high RNS, only stocks for which investors have almost exclusively opened new positions on their OTM call options subsequently outperform. In particular, only the portfolio with the highest RNS & highest OBC/T values yields a statistically significant outperformance equal to 16 bps with a t-stat of 2.63. The portfolios with the highest RNS values but with low or medium OBC/T values produce an alpha that is statistically indistinguishable to zero. Similarly, we find that among the stocks with the lowest RNS values, only the ones with the lowest OBC/T ratio subsequently underperform producing an alpha equal to -14 bps with a t-stat of -3.55.

1.9 Conclusions

This study provides and tests a possible mechanism to explain the positive relation between RNS and future stock returns by focusing on stocks with high RNS.

The mechanism is the following. Speculators may choose to trade on their optimistic beliefs or positive information in the option market, setting up leveraged long positions on stocks that they perceive to be relatively underpriced but at the same time entail substantial downside risk. In fact, we find that a portfolio of stocks that exhibit relatively high RNS (or ΔRNS) values, are underpriced, but are also exposed to pronounced downside risk subsequently yields strong outperformance.

Our findings are consistent with the theoretical arguments of Easley et al. (1998) and An et al. (2014) on cross-market predictability. Moreover, we confirm that the positive relation between RNS and future stock returns is not an artefact of a return reversal effect following stock price pressure.

Since RNS is computed from publicly observable option prices and long-only strategies face negligible limits-to-arbitrage relative to strategies involving short selling, this evidence poses a challenge to the efficient market framework. We rationalize our findings by showing that the stock outperformance predicted by a relatively high RNS (or ΔRNS) value is very short-lived. In particular, most of the documented abnormal return is earned overnight, indicating a speedy price correction process in the stock market.

1.A Definitions of Variables

Book-to-Market Value ratio (B/M)

B/M for firm i in month t is given by the ratio of Common Equity (CEQ) to Market Value. CEQ is obtained from Compustat; we use December values of year $y-1$ for the period from June of year y until May of year $y+1$. B/M is computed only for positive CEQ values.

Distance between Stock Price and Option-Implied Stock Value (DOTS)

Following Goncalves-Pinto et al. (2016), $\text{DOTS}_{i,j,d}$ is computed for stock i on day d using a pair j of American-style call and put options written on the stock i with the same maturity T and strike price $K_{i,j}$ as:

$$\text{DOTS}_{i,j,d} = \frac{S_{i,d} - \frac{S^U_{i,j,d}+S^L_{i,j,d}}{2}}{S_{i,d}},$$

where $i)$ $S_{i,d}$ is the actual price of stock i on day d, $ii)$ $S^U_{i,j,d}$ is the no-arbitrage upper bound on stock's i bid price implied by the option pair j on day d, and it is given by:

$$S^U_{i,j,d} = C^{ask}_{i,j,d} + K_{i,j} + \text{PV}_d(\text{DIV}_i) - P^{bid}_{i,j,d},$$

where $C^{ask}_{i,j,d}$ is the ask price of the call option of the pair j on day d, $\text{PV}_d(\text{DIV}_i)$ is the present value of the dividends to be paid on stock i until option expiry, and $P^{bid}_{i,j,d}$ is the bid price of the put option of the pair j, and $iii)$ $S^L_{i,j,d}$ is the no-arbitrage lower bound on stock's i ask price implied by the option pair j on day d, and it is given by:

$$S^L_{i,j,d} = C^{bid}_{i,j,d} + K_{i,j}e^{-rT} - P^{ask}_{i,j,d},$$

where $C^{bid}_{i,j,d}$ is the bid price of the call option of the pair j on day d, r is the risk-free rate, and $P^{ask}_{i,j,d}$ is the ask price of the put option of the pair j.

Finally, $\text{DOTS}_{i,d}$ for stock i on day d is given by the following weighted-average of $\text{DOTS}_{i,j,d}$ across all option pairs $j = 1, 2, ..., J$:

$$\text{DOTS}_{i,d} = 100 \frac{\sum_{j=1}^{J} \left(C^{ask}_{i,j,d} - C^{bid}_{i,j,d} + P^{ask}_{i,j,d} - P^{bid}_{i,j,d}\right)^{-1} \text{DOTS}_{i,j,d}}{\sum_{j=1}^{J} \left(C^{ask}_{i,j,d} - C^{bid}_{i,j,d} + P^{ask}_{i,j,d} - P^{bid}_{i,j,d}\right)^{-1}}$$

Estimated Shorting Fee (ESF)

To compute the ESF for firm i in month m, we use the fitted regression model of Boehme et al. (2006):

$$\begin{aligned}\text{Fee} \;=\; & 0.07834 + 0.05438\,\text{VRSI} - 0.00664\,\text{VRSI}^2 + 0.000382\,\text{VRSI}^3 - 0.5908\,\text{Option} + \\ & 0.2587\,\text{Option}\cdot\text{VRSI} - 0.02713\,\text{Option}\cdot\text{VRSI}^2 + 0.0007583\,\text{Option}\cdot\text{VRSI}^3,\end{aligned}$$

where RSI is the relative short interest and VRSI is the vicile rank of RSI (i.e. it takes the value 1 if the firm's RSI is below the 5th percentile of all firms' RSI distribution, 2 if the firm is between the 5th and 10th percentile, etc.). We obtain the short interest data from Compustat. Option is a dummy variable that takes the value 1 if there is non-zero trading volume for the firms' options in the month and 0 otherwise. Trading volume data for options are sourced from OptionMetrics.

Expected Idiosyncratic Skewness under the physical measure (EIS^P)

Following Boyer et al. (2010), to estimate EIS^P for firm i in month m, we use the fitted part of the following regression model:

$$\begin{aligned}\text{ISKEW}^P_{i,m} \;=\; & \gamma_0 + \gamma_1\text{ISKEW}^P_{i,m-60} + \gamma_2\text{IVOL}^P_{i,m-60} + \gamma_3\text{MOM}_{i,m-60} + \gamma_4\text{TURN}_{i,m-60} + \\ & + \gamma_5\text{NASD}_{i,m-60} + \gamma_6\text{SMALL}_{i,m-60} + \gamma_7\text{MED}_{i,m-60} + \Gamma\,\text{IND}_{i,m-60} + \epsilon_{i,m}\end{aligned}$$

This cross-sectional regression is estimated every month. ISKEW_i^P and IVOL_i^P denote, respectively, the idiosyncratic skewness and idiosyncratic volatility for firm i under the physical measure, computed from daily firm-level residuals of the Fama and French (1993) three-factor model over the past 60 months. MOM denotes the cumulative stock return from month $m-12$ to month $m-1$. Turn is the average monthly turnover in the past year calculated as the trading volume divided by the number of shares outstanding. Trading volume and number of shares outstanding are both obtained from CRSP. To calculate average monthly turnover, 5 valid monthly observations are required in each year. NASDAQ volume is adjusted for the double counting following Gao and Ritter (2010); NASDAQ volume is divided by 2 for the period from 1983 to January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and is unchanged from January 2004 to December 2012. NASD takes the value 1 if the firm is listed on NASDAQ and 0 otherwise. SMALL takes the value 1 if the firm is in the bottom three size deciles and 0 otherwise. MED takes the value 1 if the firm is in one of the size deciles between the fourth and the seventh and 0 otherwise. IND are a series of industry classification dummies. We use the 30 industry classifications of Fama and French (1997).

Idiosyncratic Skewness under the physical measure (ISKEW^P)

Following Boyer et al. (2010) $\text{ISKEW}_{i,m}^P$ for firm i in month m is computed as:

$$\text{ISKEW}_{i,m}^P = \frac{1}{(N(d)-2)} \frac{\sum_{t\in D} \varepsilon_{i,d}^3}{\left(\text{IVOL}_{i,m}^P\right)^3}$$

where $\varepsilon_{i,d}$ is the daily firm-level residual of the Fama and French (1993) three-factor model regression over the past 60 months, D is the set of non-missing daily returns in the past 60 months and $N(d)$ denotes the number of days in D. We require at least 15 observations in the past 60 months to compute ISKEW_i^P.

Idiosyncratic Volatility under the physical measure (IVOL^P)

$\text{IVOL}^{P}_{i,m}$ for firm i in month m is computed as:

$$\text{IVOL}^{P}_{i,m} = \left(\frac{1}{N(d)-1}\sum_{d\in D}\varepsilon^{2}_{i,d}\right)^{1/2}$$

where $\varepsilon_{i,d}$ is the daily firm-level residual of the Fama and French (1993) three-factor model regression over the past 60 months, D is the set of non-missing daily returns in the past 60 months and $N(d)$ denotes the number of days in D. We require at least 15 observations in the past 60 months to compute IVol^{P}_{i}.

Momentum (MOM)

MOM for firm i in month m is defined as its cumulative stock return from month $m-12$ to month $m-1$.

Option Relative Bid-Ask Spread (RSPREAD)

RSPREAD on day d for option j written on stock i is given by:

$$\text{RSPREAD}_{i,j,d} = \frac{\text{ASK}_{i,j,d} - \text{BID}_{i,j,d}}{(\text{ASK}_{i,j,d} + \text{BID}_{i,j,d})/2}.$$

The average RSPREAD on day d across the OTM options $j = 1, 2, ..., J$ used to compute RNS for stock i is given by:

$$\overline{\text{RSPREAD}_{i,d}} = \frac{\sum_{j=1}^{J}\text{RSPREAD}_{i,j,d}}{\#\text{options}},$$

where #options is the number of the OTM options used.

Option-to-Stock Trading Volume Ratio (O/S)

O/S on day d for firm i is given by:

$$\text{O/S}_{i,d} = \frac{\text{OPTION\_VOLUME}_{i,d}\cdot 100}{\text{STOCK\_VOLUME}_{i,d}}$$

where OPTION_VOLUME$_{i,d}$ is the total number of option contracts traded on day d, with each contract pertaining to 100 shares of firm i, and STOCK_VOLUME$_{i,d}$ is the number of shares of firm i traded on day d. To compute OPTION_VOLUME$_{i,d}$, we use all options expiring from 10 to 180 days. We then compute the average daily O/S ratio using a 12-month rolling window. To compute OPTION_VOLUME$_{i,d}$, we use all options expiring from 10 to 180 days. We then compute the average daily O/S ratio using a 12-month rolling window.

1.B Supplementary Appendix

1.B.1 Five-Factor Alphas

In the main body of the study, we measure risk-adjusted performance using FFC alphas. To address the potential concern that our benchmark results may be driven by the choice of factors to perform this risk-adjustment, this Section alternatively reports alphas estimated from the 5-factor Fama and French (2015) asset pricing model (FF5).

Similar to our benchmark analysis, we sort stocks in ascending order according to their RNS or ΔRNS values at market close every Wednesday and assign them to quintile portfolios. Their weekly equally-weighted returns are computed by compounding the corresponding daily portfolio returns from the sorting Wednesday market close until the following Wednesday market close. Table 1.A1 reports the weekly post-ranking FF5 alphas of RNS-sorted (Panel A) and ΔRNS-sorted (Panel B) quintiles.

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FF5 alpha of 18 (14) bps in the post-ranking week with a NW t-stat of 4.93 (4.54). This abnormal performance corresponds to an annualized FF5 alpha of 9.8% (7.55%). Hence, the stock outperformance predicted by relatively high RNS and ΔRNS values is much more significant, both statistically and economically, if the FF5 model is used to perform the risk-adjustment. This result derives from the fact that the highest RNS and ΔRNS quintiles actually exhibit a negative loading to the profitability (RMW) and investment (CMA) factors that the FF5 model introduces. Concluding, we confirm that the stock outperformance documented in our benchmark analysis cannot be attributed to potentially omitted risk factors.

Finally, Panel C of Table 1.A1 reports the corresponding FF5 alphas of two bivariate stock portfolios constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. In line with the results from the univariate portfolios, we find that the portfolio of stocks with the highest RNS and the highest ΔRNS values yields an FF5 alpha of 27 bps in the post-ranking week (NW t-stat: 5.21), which is greater than the corresponding FFC alpha reported in the main body of the study.

1.B.2 Friday Sorts

In our benchmark analysis, we construct portfolios on the basis of RNS and ΔRNS values at market close every Wednesday, and compute their weekly post-ranking returns until the following Wednesday market close. To examine whether the choice of the portfolio sorting day may affect our results, we alternatively construct portfolios using the corresponding RNS and ΔRNS values at market close every Friday, and compute their weekly returns by compounding the corresponding daily portfolio returns until the following Friday market close. Panel A (B) of Table 1.A2 reports the post-ranking performance of RNS-sorted (ΔRNS-sorted) quintiles.

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields an FFC alpha of 13 (10) bps in the post-ranking week, with a NW t-stat of 3.46 (2.99). If anything, the abnormal performance of the stock portfolio with the highest RNS values becomes stronger using Friday sorts. Hence, we conclude that our benchmark results are not driven by the choice of the portfolio sorting day.

1.B.3 Options with Positive Total Trading Volume

Following prior studies in the literature (see, *inter alia*, Rehman and Vilkov (2012), Stilger et al. (2017)), our benchmark analysis utilizes RNS values that are computed from OTM option prices associated with positive open interest. There is no requirement that each of these OTM options should exhibit positive trading volume. As a result, a portion of the daily RNS values in our sample have been extracted from the prices of OTM options exhibiting zero total trading volume on the corresponding day. We still expect the quoted bid-ask prices to be rather informative due to the sizeable open interest associated with these options.

Nevertheless, to alleviate the potential concern that our results may be affected by RNS values that are extracted from OTM option prices associated with zero total trading volume, we repeat the benchmark portfolio analysis excluding these RNS values. Table 1.A3 reports the weekly post-ranking performance of RNS-sorted quintile portfolios constructed at market close every Wednesday. Reflecting the exclusion of RNS values associated with zero OTM option total trading volume, each RNS-sorted quintile now consists of 109 stocks, on average, i.e., 24 fewer stocks relative to the benchmark analysis.

We find that the quintile portfolio that goes long the stocks with the highest RNS values yields an even higher FFC alpha relative to the benchmark results, which is equal to 13 bps, and is strongly significant (NW t-stat: 3.03). Hence, we conclude that the stock outperformance signalled by relatively high RNS values becomes even more pronounced when these RNS values are computed from OTM options with positive total trading volume.

1.B.4 Options Maturing in Less than Three Months

We have calculated the daily RNS for each stock in line with the studies of Rehman and Vilkov (2012), Conrad et al. (2013), and Stilger et al. (2017). In particular, we use daily prices of OTM options with 10 to 180 days-to-maturity. We discard options with zero open interest, zero bid price, negative strike, price less than \$0.50, missing implied volatility, and non-standard settlement. Furthermore, we discard horizons that do not have available at least two OTM puts and two OTM calls. Among the eligible sets of options that satisfy the above criteria, we calculate the RNS using the one with the shortest maturity.

The above methodology leads to a sufficiently large cross-section of stocks on a given day, with an average (median) of 607 (671) stocks. The average (median) RNS maturity equals 91 (94) days. In this section, we test whether our benchmark portfolio analysis holds when we consider a significantly smaller cross-section. In particular, we focus on stocks whose RNS has a horizon that is approximately less or equal to three months, excluding effectively half of our initial sample.

Table 1.A4 reports the weekly post-ranking performance of the RNS-sorted quintile portfolios constructed at the market close every Wednesday. Each portfolio contains approximately 70 stocks on average rather than 133 stocks as in our benchmark analysis. We find that the quintile portfolio that goes long the stocks with the highest RNS values yields a FFC alpha equal to 10 bps. Furthermore, even in this considerably smaller cross-section, the outperformance remains statistically significant at the five percent significance level (NW t-stat: 2.27).

1.B.5 Non-Parametric Risk-Neutral Skewness

Throughout this study, we claim that RNS captures the expensiveness of OTM calls relative to OTM puts. Hence, the ability of a relatively high RNS value to predict stock outperformance arises from the fact that the former indicates relatively expensive OTM calls due to transient price pressure in the option market.

To confirm the validity of this argument, this Section uses an alternative, direct measure of relative expensiveness between OTM calls and puts. In particular, following Bali et al. (2017), we compute a "non-parametric" proxy for RNS (NPRNS). We define NPRNS as

$$\text{NPRNS} = \frac{\text{CIV}_{20} + \text{CIV}_{25}}{2} - \frac{\text{PIV}_{-20} + \text{PIV}_{-25}}{2},$$

where CIV_{20} (CIV_{25}) is the implied volatility of the 0.20 (0.25) delta call and PIV_{-20} (PIV_{-25}) is the implied volatility of the -0.20 (-0.25) delta put. To compute NPRNS, we use the corresponding 30-day implied volatilities sourced from OptionMetrics' Volatility Surface file.

Apart from using a direct measure of relative expensiveness between OTM calls and puts, this approach serves two additional purposes. First, by alternatively using this "non-parametric" measure, we ensure that the conclusions of our benchmark analysis are not driven by the methodological choices made to compute the RNS measure of Bakshi et al. (2003). Second, by utilizing 30-day implied volatilities, we alleviate the potential concern that our benchmark results may be affected by the fact that RNS values are not computed from constant maturity OTM options.

We sort stocks in ascending order according to their NPRNS values at market close every Wednesday, and assign them to quintile portfolios. For comparability with our benchmark results, this portfolio analysis utilizes only those stocks that also have valid RNS values on the corresponding day. Table 1.A5 reports the weekly post-ranking risk-adjusted performance of the NPRNS-sorted portfolios.

In line with our benchmark results, we find a clear positive gradient in the post-ranking premia and FFC alphas as we move from the lowest NPRNS quintile to the highest NPRNS quintile. Most importantly for the focus of our study, we find that the quintile portfolio containing the stocks with the highest NPRNS values yields a significant FFC alpha of 9 bps in the post-ranking week, with a NW t-stat of 2.64. Hence, using this "non-parametric" measure, we confirm the conclusion of our benchmark analysis that the stocks with the most expensive OTM calls relative to OTM puts subsequently outperform.

We also note that the lowest NPRNS quintile subsequently yields a significant negative FFC alpha, confirming the conjecture that the relatively most expensive OTM puts predict stock underperformance. Finally, the spread between the highest and the lowest NPRNS quintiles yields an economically and statistically significant FFC alpha of 29 bps in the post-ranking week.

In unreported results, which are available upon request, we have additionally examined whether a measure of expensiveness of OTM calls relative to ATM options can also capture the positive stock information that is embedded in RNS. We term this measure R(ight)SKEW. In particular, RSKEW is defined as the difference between the implied volatility of OTM calls (deltas = 0.20 and 0.25) and the average implied volatility of ATM calls and puts (deltas $= \{0.5, 0.55\}$ and $\{-0.45, -0.5\}$, respectively).

Repeating the portfolio analysis described above, but now using RSKEW instead of NPRNS as a sorting variable, we find no evidence that the portfolio of stocks with the highest RSKEW values subsequently outperforms. This is because a relatively high RSKEW value is typically a manifestation of high Risk-Neutral Kurtosis, but it may also be associated with substantially *negative* RNS. The most obvious example of this pattern is the case of an asymmetric volatility smile, where OTM calls are more expensive than ATM options, but they are also substantially cheaper than OTM puts.

Taken together, the results of this Section confirm that it is the expensiveness of OTM calls relative to OTM puts (*not* ATM options) that can reveal positive information regarding the underlying stock. Since, by construction, a high RNS value reflects this relative expensiveness, it can also embed positive stock information.

1.B.6 Value-Weighted Portfolios

Throughout the main body of this study, we have chosen to report the results obtained from the equally-weighted portfolios rather the value-weighted portfolios as the former is indicative for the average stock, whereas the latter is mainly representative for a small number of stocks with the greatest market capitalisation in the portfolio. In our sample, consisting of 4,959 stocks, the total average market capitalisation of the top three percent (in terms of capitalisation) of the stocks is approximately equal to the average market capitalisation of the rest of the stocks. Nevertheless, to alleviate the potential concern that this choice drives our results, we repeat our benchmark analysis by forming value weighted portfolios.

In particular, every Wednesday, at market close, we sort stocks in ascending order according to their RNS values and assign them to quintile portfolios. We form value-weighted portfolios by weighing each stock in the quintile by its relative market value within the quintile. Subsequently, we compute the value-weighted return of each portfolio at market close of the following Wednesday. Table 1.A6 reports the results. We find that the results remain quantitatively and qualitatively similar to the equally-weighted portfolio sorts. In particular, the outperformance of the portfolio containing the stocks with the highest RNS values equals 13 bps (t-stat $= 3.68$).

1.B.7 Daily Rebalancing

Our benchmark analysis shows that a relatively high RNS or ΔRNS value, reflecting transient price pressure in the option market, predicts subsequent stock outperformance at the weekly frequency. Consistent with speedy price correction in the stock market, we find that this outperformance is short-lived. It is mainly earned on the first post-ranking day and, more specifically, overnight. A corollary of these findings is that, with daily rebalancing, the portfolio with the highest RNS or ΔRNS values should yield an even stronger outperformance. This Section examines the validity of this argument.

We sort stocks in ascending order according to their RNS or ΔRNS values at market close on each trading day of our sample period (i.e., a total of 4,648 trading days), and assign them to quintile portfolios. We then compute their equally-weighted returns on the next trading day. Panel A (B) of Table 1.A7 reports the daily post-ranking FFC alphas of RNS-sorted (ΔRNS-sorted) quintiles.

We find that the quintile portfolio that goes long the stocks with the highest RNS (ΔRNS) values yields a significant FFC alpha of 10 (9) bps on the *post-ranking day*, with a NW t-stat of 10.25 (11.49). Highlighting its economic significance, this abnormal performance corresponds to an annualized FFC alpha of approximately 28% (25%). Moreover, Panel C of Table 1.A7 shows that the intersection of the stocks in the highest RNS and the highest ΔRNS quintiles yields an FFC alpha of 18 bps on the post-ranking day (NW t-stat: 13.95).

These results confirm, at the daily frequency, the ability of relatively high RNS and ΔRNS values to predict stock outperformance. Additionally, these findings validate the conjecture that the documented outperformance becomes much stronger when portfolio rebalancing becomes more frequent, and hence they are consistent with the argument that it is short-lived due to speedy price correction in the stock market.

1.B.8 ΔRNS and Stock Underpricing

This Section repeats the analysis of Section IV.A in the main body of the study regarding the role of stock underpricing, using ΔRNS instead of RNS. We construct double-sorted portfolios on the basis of ΔRNS and each of the stock mispricing proxies (DOTS & MISP). To begin with, we construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their ΔRNS values at market close every Wednesday, and then, within each ΔRNS tercile, we further sort stocks into terciles according to their mispricing proxy values. Panel A.1 (B.1) of Table 1.A8 reports the weekly post-ranking risk-adjusted performance for selected equally-weighted portfolios when DOTS (MISP) is used as a mispricing proxy.

The results confirm the conclusions derived in the main body of the study. Regardless of the mispricing proxy used, we find that the outperformance of the stocks with the highest ΔRNS values is mainly driven by those stocks that are perceived to be the most underpriced. For example, the lowest DOTS tercile within the highest ΔRNS tercile yields a highly significant FFC alpha of 21 bps in the post-ranking week (NW t-stat: 4.82). To the contrary, the highest DOTS tercile within the highest ΔRNS tercile significantly underperforms. In fact, for both proxies, the spread between the most underpriced and the most overpriced stocks within the highest ΔRNS tercile yields a significant FFC alpha in the post-ranking week.

To further examine the interaction between ΔRNS and stock underpricing, we alternatively construct independent double-sorted portfolios. Panel A.2 (B.2) of Table 1.A8 reports the post-ranking performance of the corresponding portfolios when DOTS (MISP) is used as a stock mispricing proxy. The reported results corroborate the argument that the combination of a high ΔRNS value and stock underpricing strengthens subsequent outperformance. For example, we find that the intersection of the stocks with the highest ΔRNS & lowest DOTS values yields an FFC alpha of 18 bps (NW t-stat: 4.85) in the post-ranking week. To the contrary, the portfolio of stocks with the highest ΔRNS & highest DOTS values yields a highly significant negative FFC alpha.

1.B.9 ΔRNS and Stock Downside Risk

This Section repeats the analysis of Section IV.B in the main body of the study regarding the role of stock downside risk, using ΔRNS instead of RNS. We construct double-sorted portfolios on the basis of ΔRNS and each of the stock downside risk proxies (EIS^P & ESF). We initially construct bivariate conditional portfolios, where we firstly sort stocks into tercile portfolios according to their ΔRNS values at market close every Wednesday, and then, within each ΔRNS tercile, we further sort stocks into terciles according to their downside risk proxy values. Panel A.1 (B.1) of Table 1.A9 reports the weekly post-ranking FFC alphas for selected equally-weighted portfolios when EIS^P (ESF) is used as a downside risk proxy.

The results reported in Table 1.A9 are in line with the ones presented in the main body of the study. We find that the outperformance signalled by a high ΔRNS value is mainly driven by those stocks that exhibit the most pronounced downside risk. Within the highest ΔRNS tercile, the portfolio of stocks that are the most exposed to downside risk according to EIS^P (ESF) yields an FFC alpha of 14 (10) bps in the post-ranking week, with a NW t-stat of 3.64 (2.47). To the contrary, within the highest ΔRNS tercile, the portfolio of stocks characterized by the lowest exposure to downside risk does not subsequently yield significant outperformance.

We also construct independent double-sorted portfolios on the basis of ΔRNS and each of the downside risk proxies. Panel A.2 (B.2) of Table S7 reports the post-ranking performance of these independent double-sorted portfolios when EIS^P (ESF) is used as a downside risk proxy. The conclusions derived from the independent double-sorted portfolios are very similar to the ones derived from the conditional portfolio sorting approach. Regardless of the proxy used, we confirm that it is the intersection of stocks that exhibit the highest ΔRNS values and are the most exposed to downside risk which yields the strongest subsequent outperformance. To the contrary, the intersection of stocks with the highest ΔRNS values and the least pronounced downside risk does not significantly outperform.

1.B.10 ΔRNS, Stock Underpricing, and Downside Risk

This Section repeats the analysis of Section IV.C in the main body of the study, using ΔRNS instead of RNS. To this end, we construct independent triple-sorted portfolios. In particular, at market close every Wednesday, we independently sort stocks on the basis of their: *i*) ΔRNS value, *ii*) mispricing proxy value, and *iii*) downside risk proxy value, and classify them as high or low relative to the corresponding median value. The intersection of these three independent classifications yields 8 portfolios. Table 1.A10 reports their weekly post-ranking FFC alphas.

These results lead to conclusions that are similar to the ones we derived in our benchmark analysis, lending further support to the proposed trading mechanism. We find that the intersection of stocks that exhibit high ΔRNS values, are relatively underpriced, and are more exposed to downside risk (i.e., portfolio P5) yields the strongest outperformance in the post-ranking week. This pattern is robust for both mispricing proxies and both downside risk proxies. For example, the long-only portfolio of stocks with higher than median ΔRNS values, lower than median DOTS values, and lower than median EIS^P values yields an FFC alpha of 18 bps in the post-ranking week, with a NW t-stat of 4.54. To the contrary, if even one of the conditions laid out by the conjectured trading mechanism is not met, stock outperformance becomes either weaker or insignificant (see portfolios P1, P6, and P7).

1.B.11 Non Synchroneity Bias

This Section examines whether our results are affected by a non-synchronicity bias. In line with the criticism of Battalio and Schultz (2006), there is the potential concern that the RNS values that we use to form portfolios at the end of the trading day may not be available to investors in a timely manner that allows them to form the portfolios in the equities market. Firstly, the non-synchronicity issue is not as important for equity options as it is for options written on an index. The CBOE equity options market closes virtually simultaneously with the underlying stock market at 4 pm (EST). This is in contrast to the S&P 500 option market, which closes at 4.15 pm (EST). Furthermore, since March 5, 2008, OptionMetrics reports the best (or highest) 3:59pm (EST) bid and offer prices across all exchanges on which the option trades. Hence, after March 5, 2008, the RNS values we use are available to investors one minute before the close of the equities market.

In the main body of the study, we find that the outperformance that is signalled by a relatively high RNS is earned predominantly overnight. To test whether the change of the data recording time affects this result, we repeat the decomposition of the first post-ranking day return for two sub periods. The first period ranges from January 1996 to February 2008, and the second period ranges from April 2008 to June 2014. The second period starts one month after OptionMetrics changed the data recording time. Table A.11 presents the results. We find that the overnight FF4 alpha of the portfolio containing the stocks with the highest RNS values is highly statistically significant in both periods. In particular, the performance of the portfolio containing the stocks with the highest RNS values before March 2008 equals 16 bps (t-stat = 9.93) and after March 2008 equals 5 bps (t-stat = 4.01). We believe that the lower performance of the portfolio during the second period is likely due to the electrification of the financial markets. The first period coincides with a period where the United States trading volume due to algorithmic trading rises from a point near zero to 73 percent (see Hendershott, Jones, and Menkveld, 2011). We can only assume that in the second period algorithmic trading is even more prominent.

Table 1.1: Descriptive Statistics

This Table reports descriptive statistics for the set of the out-of-the-money (OTM) call and put options used to compute permno-day Risk-Neutral Skewness (RNS) estimates during the period January 1996–June 2014. Moneyness denotes the ratio of the underlying stock price to the strike price of the OTM call and put option, respectively. Average moneyness is computed across the OTM options used per permno-day RNS estimate. Total open interest refers to the number of open contracts for the OTM options used per permno-day RNS estimate. Each contract pertains to 100 shares. RSPREAD is the relative bid-ask spread of the OTM option used. Average RSPREAD is computed across the OTM options used per permno-day RNS estimate. The total number of permno-day RNS estimates is 3,121,205.

	Mean	St. Dev.	5th pctl	25th pctl	Median	75th pctl	95th pctl
RNS	-0.4113	0.3193	-0.9453	-0.5831	-0.3889	-0.2136	0.0376
Days to expiration of OTM options per RNS estimate	91.81	47.36	23	46	94	130	169
Average moneyness of OTM call options	0.8928	0.0585	0.7851	0.8606	0.9031	0.9364	0.9670
Average moneyness of OTM put options	1.1496	0.0852	1.0472	1.0887	1.1332	1.1917	1.3054
No. of OTM options per RNS estimate	5.55	2.62	4	4	5	6	9
Total open interest of OTM options	7,312.61	20,225.40	154	609	1,838	6,075	30,359
Average RSPREAD of OTM options	0.1848	0.1557	0.0404	0.1029	0.1461	0.2132	0.4539
No. of permnos with RNS estimate per day	671.08	221.62	346	468	671	864	1,012

Table 1.2: Rank Correlation Coefficients

This Table reports the time-series averages of weekly pairwise Spearman's rank correlation coefficients. For each pair of variables, their rank correlation coefficient is computed every Wednesday, i.e., the benchmark portfolio-sorting day. The sample period is January 1996–June 2014. RNS is the Risk-Neutral Skewness, and ΔRNS is the change in the RNS estimate relative to the previous trading day. MV stands for firm market value. B/M denotes firm book-to-market value ratio. MOM is the cumulative stock return from month *t-12* to month *t-1*. DOTS is the distance between the actual stock price and the option-implied stock value computed as in Goncalves-Pinto et al. (2016). MISP denotes the composite mispricing rank of Stambaugh and Yuan (2016). EIS^P stands for the expected idiosyncratic skewness of daily stock returns under the physical measure computed as in Boyer et al. (2010). ESF denotes the estimated shorting fee for each stock computed as in Boehme et al. (2006). RET(1) is the daily stock return. RET(5) is the cumulative 5-day stock return. RSPREAD denotes the average relative bid-ask spread of the out-of-the-money options used to compute RNS. O/S stands for the average daily option-to-stock trading volume ratio over the previous 12 months. For the variables that are available at daily frequency, their Wednesday values are used. For the variables that are available at monthly frequency, their end-of-month values prior to each Wednesday are used.

	RNS	ΔRNS	MV	B/M	MOM	DOTS	MISP	EIS^P	ESF	RET(1)	RET(5)	RSPREAD	O/S
RNS	1												
ΔRNS	0.27	1											
MV	-0.31	0.00	1										
B/M	-0.05	0.00	-0.24	1									
MOM	-0.00	-0.00	0.23	-0.39	1								
DOTS	-0.31	-0.31	-0.02	0.00	-0.01	1							
MISP	0.12	-0.00	-0.21	0.14	-0.32	0.02	1						
EIS^P	0.10	0.00	-0.48	-0.02	-0.00	0.01	0.13	1					
ESF	0.09	-0.00	0.08	-0.08	-0.05	0.05	0.17	-0.04	1				
RET(1)	-0.06	-0.19	0.02	-0.00	0.02	0.15	-0.01	-0.01	-0.01	1			
RET(5)	-0.05	-0.04	0.03	-0.01	0.03	0.08	-0.02	-0.01	-0.01	0.40	1		
RSPREAD	0.01	-0.01	-0.43	0.02	0.03	0.02	0.06	0.17	0.09	-0.01	-0.01	1	
O/S	-0.01	-0.00	0.08	-0.19	-0.00	0.02	0.06	0.05	0.16	-0.01	-0.01	-0.43	1

Table 1.3: Characteristics of RNS and ΔRNS-sorted Weekly Quintile Portfolios

This Table reports the average characteristics of quintile stock portfolios sorted on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A) or the change in their RNS (ΔRNS) estimate relative to previous trading day (Panel B). The portfolio sorting is performed every Wednesday. The sample period is January 1996–June 2014. MV stands for firm market value. B/M denotes firm book-to-market value ratio. MOM is the cumulative stock return from month *t-12* to month *t-1*, winsorized at the 95^{th} percentile. DOTS is the distance between the actual stock price and the option-implied stock value computed as in Goncalves-Pinto et al. (2016). MISP denotes the composite mispricing rank of Stambaugh and Yuan (2016). EIS^{P} stands for the expected idiosyncratic skewness of daily stock returns under the physical measure computed as in Boyer et al. (2010). ESF denotes the estimated shorting fee for each stock computed as in Boehme et al. (2006). RET(1) denotes the stock return on the sorting day. RET(5) denotes the cumulative 5-day stock return up to the sorting day. RSPREAD denotes the average relative bid-ask spread of the out-of-the-money options used to compute RNS. O/S stands for the average daily option-to-stock trading volume ratio over the previous 12 months. For the variables that are available at daily frequency, their sorting-day values are used. For the variables that are available at monthly frequency, their end-of-month values prior to the sorting day are used. The last line shows the difference (spread) between the portfolio with the highest RNS or ΔRNS stocks and the portfolio with lowest RNS or ΔRNS stocks in each case. **, and * indicate statistical significance of the spread at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios													
	RNS	ΔRNS	LN(MV)	B/M	MOM	DOTS	MISP	EIS^{P}	ESF	RET(1)	RET(5)	RSPREAD	O/S
1 (Lowest RNS)	-0.79	-0.07	22.62	0.38	22.40%	0.20	46.86	0.74	0.61	0.25%	0.70%	0.19	11.80%
2	-0.51	-0.02	22.24	0.39	24.62%	0.08	47.08	0.75	0.61	0.19%	0.55%	0.17	10.73%
3	-0.37	-0.00	21.93	0.38	26.09%	0.03	47.99	0.78	0.64	0.15%	0.45%	0.17	10.83%
4	-0.26	0.02	21.65	0.37	26.30%	-0.03	49.29	0.82	0.66	0.08%	0.33%	0.17	11.14%
5 (Highest RNS)	-0.07	0.08	21.28	0.38	25.67%	-0.18	51.36	0.90	0.69	-0.11%	0.08%	0.18	11.89%
Spread (5-1)	0.72**	0.14**	-1.35**	-0.00	3.27%*	-0.37**	4.49**	0.16**	0.08**	-0.36%**	-0.62%**	-0.01	0.08%

Table 1.3: (Continued)

Panel B: ΔRNS-sorted Quintile Portfolios													
	ΔRNS	RNS	LN(MV)	B/M	MOM	DOTS	MISP	EIS^P	ESF	RET(1)	RET(5)	RSPREAD	O/S
1 (Lowest ΔRNS)	-0.21	-0.51	21.95	0.37	26.96%	0.16	48.57	0.80	0.64	0.78%	0.81%	0.20	11.88%
2	-0.06	-0.43	22.00	0.38	24.56%	0.08	48.43	0.79	0.64	0.36%	0.56%	0.16	10.93%
3	0.00	-0.40	22.02	0.38	24.12%	0.03	48.34	0.78	0.64	0.03%	0.33%	0.15	11.52%
4	0.06	-0.37	22.00	0.39	24.48%	-0.03	48.40	0.78	0.64	-0.25%	0.11%	0.16	11.26%
5 (Highest ΔRNS)	0.22	-0.30	21.96	0.37	26.71%	-0.14	48.49	0.80	0.64	-0.55%	0.06%	0.19	12.11%
Spread (5-1)	0.43**	0.21**	0.01	-0.00	-0.25%	-0.30**	-0.08	0.00	-0.00	-1.32%**	-0.74%**	-0.00*	0.23%

Table 1.4: RNS and ΔRNS-sorted Weekly Quintile Portfolio Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), and the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line in Panel A (Panel B) reports the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	0.04	-0.12**	1.08**	0.30**	-0.07*	-0.04	0.93	134
		(-4.57)						
2	0.11	-0.07*	1.16**	0.38**	-0.13**	-0.04*	0.94	133
		(-2.45)						
3	0.13	-0.05	1.22**	0.53**	-0.18**	-0.06**	0.93	133
		(-1.73)						
4	0.21	0.01	1.29**	0.63**	-0.23**	-0.08**	0.92	133
		(0.47)						
5 (Highest RNS)	0.32*	0.12**	1.35**	0.78**	-0.28**	-0.14**	0.90	134
		(3.11)						
Spread (5-1)	0.27**	0.24**	0.27**	0.47**	-0.20**	-0.09	0.39	
t(5-1)	(4.34)	(5.03)	(11.78)	(8.73)	(-4.05)	(-1.93)		

Panel B: ΔRNS-sorted Quintile Portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest ΔRNS)	0.03	-0.16**	1.23**	0.55**	-0.24**	-0.06**	0.92	125
		(-4.50)						
2	0.12	-0.07*	1.21**	0.53**	-0.14**	-0.06*	0.93	125
		(-2.34)						
3	0.15	-0.03	1.22**	0.50**	-0.17**	-0.08**	0.93	125
		(-1.18)						
4	0.20	0.01	1.22**	0.50**	-0.17**	-0.07**	0.93	125
		(0.49)						
5 (Highest ΔRNS)	0.29*	0.10**	1.25**	0.50**	-0.22**	-0.06*	0.92	125
		(3.15)						
Spread (5-1)	0.26**	0.25**	0.02	-0.04	0.02	0.00	0.01	
t(5-1)	(6.60)	(6.65)	(1.09)	(-1.54)	(0.72)	(0.16)		

Table 4: (Continued)

Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios								
RNS 1 (Lowest) & ΔRNS 1 (Lowest)	-0.02	-0.19** (-4.41)	1.12**	0.41**	-0.13**	-0.04	0.85	41
RNS 5 (Highest) & ΔRNS 5 (Highest)	0.41**	0.21** (4.03)	1.34**	0.69**	-0.30**	-0.09*	0.85	43
Spread (5&5-1&1)	0.43**	0.40**	0.23**	0.28**	-0.16*	-0.05	0.17	
t(5&5- 1&1)	(5.79)	(5.80)	(7.18)	(5.63)	(-2.36)	(-0.96)		

Table 1.5: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Stock Mispricing

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two stock mispricing proxies used. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016) in Panel A, and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016) in Panel B. A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to their Wednesday DOTS values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their RNS estimates and their Wednesday DOTS values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these RNS- and stock mispricing-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: DOTS

Panel A.1: Conditional Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)	Panel A.2: Independent Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	0.02	-0.29**	0.32**	RNS 1 (Lowest)	0.06	-0.23**	0.29**
	(0.82)	(-6.48)	(6.48)		(1.35)	(-6.08)	(5.96)
					[44]	[95]	
RNS 3 (Highest)	0.29**	-0.14**	0.43**	RNS 3 (Highest)	0.23**	-0.18**	0.40**
	(5.98)	(-3.34)	(7.90)		(5.85)	(-3.33)	(7.14)
					[106]	[47]	
Spread (3-1)	0.27**	0.15**		Spread (3-1)	0.17**	0.05	
	(5.15)	(2.61)			(3.22)	(0.82)	

Panel B: MISP

Panel B.1: Conditional Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)	Panel B.2: Independent Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	-0.01	-0.25**	0.24**	RNS 1 (Lowest)	-0.01	-0.26**	0.25**
	(-0.50)	(-5.85)	(5.06)		(-0.50)	(-6.03)	(5.36)
					[81]	[59]	
RNS 3 (Highest)	0.15**	0.01	0.14*	RNS 3 (Highest)	0.15**	0.05	0.10
	(3.94)	(0.10)	(2.35)		(4.00)	(0.93)	(1.84)
					[57]	[83]	
Spread (3-1)	0.16**	0.25**		Spread (3-1)	0.16**	0.31**	
	(4.01)	(4.44)			(4.18)	(5.60)	

Table 1.6: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010) in Panel A, and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006) in Panel B. A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to tercile portfolios. Within each RNS tercile portfolio, we further sort stocks according to their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.1) or ESF values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their RNS estimates and their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.2) or ESF values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these RNS- and stock downside risk-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: EIS^P

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)		EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	0.01	-0.15**	0.16**	RNS 1 (Lowest)	-0.00	-0.17**	0.16**
	(0.29)	(-4.12)	(3.16)		(-0.05)	(-4.28)	(2.94)
					[59]	[48]	
RNS 3 (Highest)	0.17**	-0.01	0.17**	RNS 3 (Highest)	0.17**	0.01	0.16**
	(3.77)	(-0.15)	(3.05)		(3.60)	(0.27)	(2.92)
					[51]	[68]	
Spread (3-1)	0.16**	0.15*		Spread (3-1)	0.17**	0.18**	
	(3.41)	(2.43)			(3.48)	(3.08)	

Panel B: ESF

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	ESF Lowest	ESF Highest	Spread (Lowest-Highest)		ESF Lowest	ESF Highest	Spread (Lowest-Highest)
RNS 1 (Lowest)	-0.02	-0.19**	0.17**	RNS 1 (Lowest)	-0.02	-0.22**	0.20**
	(-0.71)	(-4.35)	(4.03)		(-0.67)	(-4.57)	(4.35)
					[73]	[48]	
RNS 3 (Highest)	0.11*	-0.05	0.16**	RNS 3 (Highest)	0.10*	-0.02	0.12*
	(2.35)	(-0.89)	(2.92)		(2.17)	(-0.36)	(2.30)
					[58]	[64]	
Spread (3-1)	0.13**	0.14**		Spread (3-1)	0.12**	0.20**	
	(2.98)	(2.59)			(2.70)	(3.68)	

Table 1.7: Trivariate Independent Portfolio Sorts: RNS, Stock Mispricing and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of trivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates, each of the two proxies used for stock mispricing, and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016), and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016). A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010), and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006). A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. Every Wednesday, at market close, stocks are independently sorted in ascending order according to: 1) their RNS estimates, 2) their Wednesday DOTS values or their end-of-month, prior to the sorting Wednesday, MISP values, and 3) their end-of-month, prior to the sorting Wednesday, EIS^P or ESF values, and they are classified for each sorting criterion as Low (L) or High (H) relative to the corresponding median value. The intersections of these three classifications yield 8 portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. The average number of stocks per portfolio is reported in square brackets. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

	Stock Mispricing Proxy	DOTS		MISP	
	Downside Risk Proxy	EIS^P	ESF	EIS^P	ESF
P1	RNS Low & DOTS/ MISP Low & EIS^P/ ESF Low	0.11** (2.91) [55]	0.06 (1.74) [69]	0.05 (1.49) [79]	0.03 (1.22) [95]
P2	RNS Low & DOTS/ MISP Low & EIS^P/ ESF High	-0.03 (-0.77) [45]	-0.02 (-0.59) [37]	-0.02 (-0.64) [58]	-0.06 (-1.27) [46]
P3	RNS Low & DOTS/ MISP High & EIS^P/ ESF Low	-0.07* (-2.03) [76]	-0.03 (-1.08) [86]	-0.04 (-0.94) [53]	-0.03 (-1.00) [57]
P4	RNS Low & DOTS/ MISP High & EIS^P/ ESF High	-0.20** (-5.84) [70]	-0.24** (-5.71) [70]	-0.22** (-5.50) [59]	-0.19** (-4.39) [59]
P5	RNS High & DOTS/ MISP Low & EIS^P/ ESF Low	0.22** (4.92) [70]	0.16** (3.84) [79]	0.15** (3.76) [59]	0.13** (2.86) [67]
P6	RNS High & DOTS/ MISP Low & EIS^P/ ESF High	0.12** (2.98) [76]	0.09 (1.92) [78]	0.07 (1.78) [54]	0.01 (0.28) [49]
P7	RNS High & DOTS/ MISP High & EIS^P/ ESF Low	-0.04 (-0.89) [45]	-0.04 (-0.80) [47]	0.11* (2.33) [58]	0.08 (1.62) [55]
P8	RNS High & DOTS/ MISP High & EIS^P/ ESF High	-0.17** (-3.52) [54]	-0.20** (-3.90) [59]	-0.01 (-0.12) [77]	-0.00 (-0.05) [85]

Table 1.8: Bivariate Portfolio Sorts: Risk-Neutral Skewness and Option Liquidity

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and each of the two proxies used for option liquidity. The sample period is January 1996–June 2014. We use the following two proxies for option liquidity: i) the average relative bid-ask spread (RSPREAD) of the OTM options used to compute these RNS estimates in Panel A, and ii) the average daily option-to-stock trading volume ratio (O/S) over the previous 12 months in Panel B. A high value of RSPREAD indicates that the OTM options are illiquid. A low value of O/S indicates that the options are illiquid relative to the underlying stock. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their RNS estimates and they are assigned to quintile portfolios. Within each RNS quintile portfolio, we further sort stocks according to their Wednesday RSPREAD values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, O/S values (Panel B.1), and classify them into two portfolios: i) Low, if the RSPREAD (O/S) value is below the 80^{th} (20^{th}) percentile of the corresponding cross-sectional distribution, or ii) High, if the RSPREAD (O/S) value is above the 80^{th} (20^{th}) percentile. Results are reported only for the portfolios within the lowest and the highest RNS quintiles. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted into quintile portfolios according to their RNS estimates, and into two portfolios according to their Wednesday RSPREAD values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, O/S values (Panel B.2): i) Low, if the RSPREAD (O/S) value is below the 80^{th} (20^{th}) percentile of the corresponding cross-sectional distribution, or ii) High, if the RSPREAD (O/S) value is above the 80^{th} (20^{th}) percentile. The intersections of these RNS- and option liquidity-sorted portfolios yield the independent portfolios. Results are reported only for the intersections that involve the lowest and the highest RNS quintiles. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RSPREAD

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	RSPREAD Low	RSPREAD High	Spread		RSPREAD Low	RSPREAD High	Spread
RNS 1 (Lowest)	-0.12**	-0.14**	0.02	RNS 1 (Lowest)	-0.12**	-0.16**	0.04
	(-4.37)	(-2.90)	(0.51)		(-4.26)	(-3.17)	(0.83)
					[102]	[32]	
RNS 5 (Highest)	0.14**	0.03	0.11	RNS 5 (Highest)	0.14**	0.05	0.10
	(3.45)	(0.41)	(1.59)		(3.45)	(0.76)	(1.35)
					[103]	[31]	
Spread (5-1)	0.26**	0.17*		Spread (5-1)	0.26**	0.21**	
	(5.06)	(2.21)			(5.05)	(2.73)	

Panel B: O/S

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	O/S High	O/S Low	Spread		O/S High	O/S Low	Spread
RNS 1 (Lowest)	-0.13**	-0.09*	-0.04	RNS 1 (Lowest)	-0.14**	-0.08	-0.06
	(-4.50)	(-2.08)	(-0.85)		(-4.77)	(-1.83)	(-1.27)
					[100]	[25]	
RNS 5 (Highest)	0.12**	0.02	0.10	RNS 5 (Highest)	0.13**	0.01	0.12
	(2.84)	(0.45)	(1.64)		(2.98)	(0.14)	(1.90)
					[102]	[24]	
Spread (5-1)	0.25**	0.12		Spread (5-1)	0.27**	0.09	
	(4.63)	(1.87)			(4.87)	(1.42)	

Table 1.9: RNS and ΔRNS-sorted Portfolios: Decomposing Weekly Returns

This Table reports a decomposition of the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. We compute: i) equally-weighted portfolio returns at market close of the first post-ranking trading day, and ii) equally-weighted portfolio returns at market close of the following Wednesday skipping the first post-ranking trading day. Ex Ret denotes the average portfolio return for the corresponding holding period in excess of the risk-free rate. α_{FFC} denotes the portfolio alpha for the corresponding holding period estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

First Post-Ranking Trading Day			Skip First Post-Ranking Trading Day		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ex Ret	α_{FFC}
1 (Lowest RNS)	0.01	-0.05**	1 (Lowest RNS)	0.03	-0.07**
		(-4.76)			(-2.97)
2	0.03	-0.04**	2	0.08	-0.02
		(-3.31)			(-0.92)
3	0.06	-0.02	3	0.08	-0.03
		(-1.40)			(-1.15)
4	0.12*	0.03	4	0.09	-0.01
		(1.83)			(-0.38)
5 (Highest RNS)	0.19**	0.09**	5 (Highest RNS)	0.13	0.03
		(4.21)			(0.91)
Spread (5-1)	0.18**	0.14**	Spread (5-1)	0.10	0.10*
t(5-1)	(5.81)	(5.86)	t(5-1)	(1.85)	(2.43)

Panel B: ΔRNS-sorted Quintile Portfolios

First Post-Ranking Trading Day			Skip First Post-Ranking Trading Day		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ex Ret	α_{FFC}
1 (Lowest ΔRNS)	0.01	-0.08**	1 (Lowest ΔRNS)	0.03	-0.08**
		(-4.75)			(-2.58)
2	0.04	-0.04**	2	0.08	-0.03
		(-2.67)			(-1.14)
3	0.07	-0.01	3	0.08	-0.02
		(-0.49)			(-0.85)
4	0.11*	0.03	4	0.09	-0.01
		(1.95)			(-0.41)
5 (Highest ΔRNS)	0.17**	0.09**	5 (Highest ΔRNS)	0.12	0.01
		(5.23)			(0.50)
Spread (5-1)	0.17**	0.17**	Spread (5-1)	0.09**	0.09**
t(5-1)	(8.53)	(8.55)	t(5-1)	(3.07)	(3.03)

Table 1.10: RNS and ΔRNS-sorted Portfolios: Decomposing First Post-Ranking Day Returns

This Table reports a decomposition of the first post-ranking trading day performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile equally-weighted portfolios. We compute: i) overnight portfolio returns from the market close of the ranking day (Wednesday) to the market open of the first post-ranking trading day, and ii) intraday portfolio returns from the market open to the market close of the first post-ranking trading day. Ex Ret denotes the average portfolio return in excess of the risk-free rate. The risk-free rate is deducted only from the overnight portfolio return. α_{FFC} denotes the portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model, using the corresponding overnight and intraday factor returns. Returns and alphas are expressed in percentages. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios

	Overnight Performance			Intraday Performance	
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest RNS)	-0.02	-0.05**	1 (Lowest RNS)	0.03	-0.01
		(-6.59)			(-0.58)
2	0.00	-0.03**	2	0.03	-0.01
		(-3.94)			(-1.07)
3	0.03	-0.00	3	0.03	-0.02
		(-0.52)			(-1.36)
4	0.08**	0.05**	4	0.04	-0.02
		(5.01)			(-1.01)
5 (Highest RNS)	0.18**	0.13**	5 (Highest RNS)	0.01	-0.05**
		(9.69)			(-2.64)
Spread (5-1)	0.20**	0.18**	Spread (5-1)	-0.02	-0.04*
t(5-1)	(10.67)	(10.94)	t(5-1)	(-0.86)	(-2.01)

Panel B: ΔRNS-sorted Quintile Portfolios

	Overnight Performance			Intraday Performance	
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest ΔRNS)	-0.01	-0.05**	1 (Lowest ΔRNS)	0.02	-0.03*
		(-4.56)			(-2.15)
2	0.02	-0.01	2	0.02	-0.03*
		(-1.28)			(-2.32)
3	0.05	0.01	3	0.03	-0.02
		(1.94)			(-1.63)
4	0.07**	0.04**	4	0.03	-0.01
		(5.12)			(-1.03)
5 (Highest ΔRNS)	0.13**	0.10**	5 (Highest ΔRNS)	0.04	-0.01
		(8.30)			(-0.69)
Spread (5-1)	0.14**	0.15**	Spread (5-1)	0.02	0.02
t(5-1)	(9.40)	(9.48)	t(5-1)	(1.53)	(1.56)

Table 1.11: Bivariate Conditional Portfolio Sorts: Return Reversals and Risk-Neutral Skewness

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of their cumulative returns up to the sorting day and their Risk-Neutral Skewness (RNS) estimates. The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their: i) Wednesday return (RET(1)) in Panel A, ii) cumulative 3-day return up to Wednesday (RET(3)) in Panel B, and iii) cumulative 5-day return up to Wednesday (RET(5)) in Panel C, and they are assigned to tercile portfolios. Within each cumulative stock return tercile portfolio, we further sort stocks according to their RNS estimates, and construct quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Weekly portfolio alphas (in percentages) are estimated from the Fama-French-Carhart (FFC) 4-factor model. Mean RET(1), Mean RET(3), and Mean RET(5) denote the average RET(1), RET(3), and RET(5) values, respectively, for the stocks in each cumulative stock return tercile portfolio. Alphas are reported for each cumulative stock return tercile across all RNS quintiles as well as for the lowest and the highest RNS quintiles within each cumulative stock return tercile. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RET(1)

	Mean RET(1)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(1) Low	-0.02**	0.02	-0.16**	0.26**	0.42**
		(0.72)	(-3.77)	(4.37)	(6.25)
RET(1) Medium	0.00	-0.02	-0.11**	0.04	0.15**
		(-1.13)	(-3.53)	(0.98)	(2.92)
RET(1) High	0.03**	-0.06	-0.11**	0.04	0.16*
		(-1.74)	(-2.79)	(0.75)	(2.34)
Spread (Low-High)	-0.05**	0.09	-0.05	0.21**	
		(1.79)	(-0.91)	(2.68)	

Panel B: RET(3)

	Mean RET(3)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(3) Low	-0.04**	0.09*	-0.07	0.30**	0.37**
		(2.34)	(-1.44)	(4.41)	(5.03)
RET(3) Medium	0.00	0.00	-0.09**	0.07	0.16**
		(0.11)	(-2.90)	(1.58)	(3.14)
RET(3) High	0.05**	-0.16**	-0.22**	-0.07	0.15*
		(-4.29)	(-5.07)	(-1.36)	(2.46)
Spread (Low-High)	-0.09**	0.25**	0.15*	0.37**	
		(4.23)	(2.32)	(4.19)	

Table 1.11: (Continued)

Panel B: RET(5)					
	Mean RET(5)	All RNS Quintiles	RNS 1 (Lowest)	RNS 5 (Highest)	Spread (5-1)
RET(5) Low	-0.05**	0.10*	-0.10	0.34**	0.45**
		(2.36)	(-1.95)	(5.54)	(6.21)
RET(5) Medium	0.00*	0.01	-0.07*	0.13**	0.19**
		(0.28)	(-2.55)	(2.61)	(3.41)
RET(5) High	0.06**	-0.16**	-0.21**	-0.10	0.11
		(-4.54)	(-4.36)	(-1.69)	(1.69)
Spread (Low-High)	-0.12**	0.26**	0.11	0.44**	
		(4.41)	(1.47)	(5.26)	

Table 1.12: Risk-Neutral Skewness and Option Trading Activity

This Table reports the weekly post-ranking performance of portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates and their ratio of the International Securities Exchange (ISE) open buy out-of-the-money call option's volume to total ISE OTM option's volume (OBC/T). The sample period is May 2005 – June 2014, excluding the last quarter of 2008 covering the short-sale ban during the financial crisis. In Panel A, every Wednesday, at market close, stocks are sorted into three portfolios according to their OBC/T values: i) Low, if the OBC/T value is below the 40^{th} percentile, ii) Medium, if the OBC/T value is between the 40^{th} and 60^{th}, and iii) High, if the OBC/T value is above the 60^{th} percentile of the corresponding cross-sectional distribution. In Panel B, stocks are assigned to the intersections of the aforementioned OBC/T portfolios and RNS tercile portfolios. Results are reported only for the lowest/highest and the intersections involving the lowest/highest RNS- and OBC/T-sorted portfolios. For each portfolio, the corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). ($\overline{\mathrm{OBC/T}}$) denotes the average OBC/T value of the stocks in the corresponding portfolio. Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line in Panels A shows the spread between the portfolio with the highest OBC/T stocks and the portfolio with lowest OBC/T stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: OBC/T-sorted portfolios

Quintiles	$\overline{\mathrm{OBC/T}}$	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
OBC/T 1	16%	0.15	-0.05	1.17**	0.36**	0.02	-0.05	0.95	162
(Lowest)			(-1.75)						
OBC/T 3	97%	0.29*	0.08*	1.25**	0.38**	-0.09	-0.04	0.83	161
(Highest)			(2.17)						
Spread (3-1)		0.14**	0.13**	0.08**	0.02	-0.11	0.02	0.25	
t(3-1)		(4.11)	(3.85)	(2.79)	(0.42)	(-1.89)	(0.63)		

Panel B: Bivariate Independent RNS and OBC/T sorts

Portfolio	$\overline{\mathrm{OBC/T}}$	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
RNS 1 – OBC/T 1	15%	0.13	-0.14**	1.07**	0.30**	-0.03	-0.08**	0.91	62
			(-3.55)	(-3.55)					
RNS 1 – OBC/T 2	67%	0.18	-0.08	1.06**	0.18**	-0.11	-0.04	0.81	24
			(-1.69)						
RNS 1 – OBC/T 3	97%	0.24	-0.02	1.04**	0.30**	-0.11**	-0.03	0.92	47
			(-0.55)						
RNS 3 – OBC/T 1	19%	0.38**	0.06	1.24**	0.42**	0.24**	-0.01	0.85	44
			(0.86)						
RNS 3 – OBC/T 2	69%	0.39**	0.05	1.39**	0.29**	-0.06	0.05	0.77	30
			(0.59)						
RNS 3 – OBC/T 3	97%	0.50**	0.16**	1.39**	0.52**	-0.00	0.03	0.84	59
			(2.63)						

Table 1.A1: RNS and ΔRNS-sorted Quintile Portfolios: Five-factor Alphas

This Table reports the weekly post-ranking risk-adjusted performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). α_{FF5} denotes the weekly portfolio alpha estimated from the Fama-French 5-factor (FF5) model. Alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML), profitability (RMW) and investment (CMA) factors estimated from the FF5 model as well as its adjusted R^2 (R^2 adj.). The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

	Panel A: RNS-sorted quintile portfolios						
Quintiles	α_{FF5}	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2 adj.
RNS 1	-0.12**	1.07**	0.29**	-0.01	-0.05	-0.11*	0.93
	(-4.34)						
2	-0.06*	1.15**	0.36**	-0.04	-0.05	-0.16**	0.94
	(-2.22)						
3	-0.02	1.17**	0.47**	-0.03	-0.18**	-0.26**	0.93
	(-0.78)						
4	0.05	1.23**	0.55**	-0.03	-0.24**	-0.31**	0.93
	(1.61)						
RNS 5	0.18**	1.25**	0.63**	0.01	-0.46**	-0.41**	0.92
	(4.93)						
Spread (5-1)	0.29**	0.18**	0.34**	0.02	-0.42**	-0.30**	0.45
t(5-1)	(6.29)	(7.30)	(7.24)	(0.21)	(-4.72)	(-3.25)	
	Panel B: ΔRNS-sorted quintile portfolios						
ΔRNS 1	-0.12**	1.17**	0.48**	-0.07*	-0.22**	-0.27**	0.93
	(-3.66)						
2	-0.04	1.17**	0.46**	-0.01	-0.20**	-0.21**	0.94
	(-1.52)						
3	-0.01	1.17**	0.44**	-0.01	-0.19**	-0.26**	0.94
	(-0.24)						
4	0.04	1.16**	0.43**	-0.01	-0.22**	-0.25**	0.93
	(1.73)						
ΔRNS 5	0.14**	1.18**	0.43**	-0.03	-0.24**	-0.30**	0.93
	(4.54)						
Spread (5-1)	0.26**	0.01	-0.05	0.04	-0.02	-0.04	0.00
t(5-1)	(6.72)	(0.58)	(-1.57)	(1.19)	(-0.43)	(-0.74)	
Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios							
RNS 1 (Lowest) & ΔRNS 1 (Lowest)	-0.18**	1.09**	0.38**	-0.05	-0.09	-0.15	0.86
	(-4.06)						
RNS 5 (Highest) & ΔRNS 5 (Highest)	0.27**	1.25**	0.56**	-0.05	-0.39**	-0.38**	0.86
	(5.21)						
Spread (5&5- 1&1)	0.45**	0.15**	0.18**	-0.00	-0.30**	-0.24*	0.20
t(5&5- 1&1)	(6.43)	(4.90)	(4.06)	(-0.05)	(-3.34)	(-2.29)	

Table 1.A2: RNS and ΔRNS-sorted Quintile Portfolios: Friday Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Friday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), or the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Every Friday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Friday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line in Panel A (Panel B) shows the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted quintile portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	-0.00	-0.17**	1.07**	0.29**	-0.06	-0.03	0.92	133
		(-5.84)						
2	0.13	-0.05*	1.14**	0.39**	-0.09**	-0.05*	0.94	133
		(-1.98)						
3	0.14	-0.05	1.20**	0.57**	-0.14**	-0.06*	0.93	133
		(-1.95)						
4	0.21	0.01	1.25**	0.68**	-0.18**	-0.08**	0.92	133
		(0.42)						
5 (Highest RNS)	0.33*	0.13**	1.34**	0.81**	-0.27**	-0.18**	0.90	133
		(3.46)						
Spread (5-1)	0.33**	0.30**	0.27**	0.52**	-0.20**	-0.15**	0.41	
t(5-1)	(5.18)	(5.94)	(8.27)	(9.39)	(-3.40)	(-3.11)		

Panel B: ΔRNS-sorted quintile portfolios

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest ΔRNS)	-0.01	-0.19**	1.21**	0.55**	-0.24**	-0.07**	0.92	125
		(-5.37)						
2	0.08	-0.10**	1.18**	0.58**	-0.15**	-0.09**	0.93	124
		(-3.71)						
3	0.19	0.01	1.20**	0.51**	-0.11**	-0.08**	0.93	124
		(0.18)						
4	0.25*	0.07*	1.20**	0.52**	-0.12**	-0.07**	0.93	124
		(2.23)						
5 (Highest ΔRNS)	0.28*	0.10**	1.21**	0.52**	-0.19**	-0.10**	0.92	124
		(2.99)						
Spread (5-1)	0.28**	0.28**	0.00	-0.03	0.06	-0.02	0.01	
t(5-1)	(6.72)	(6.71)	(0.20)	(-1.13)	(1.33)	(-1.29)		

Table 1.A3: RNS-sorted Quintile Portfolios: OTM Options with Positive Trading Volume

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates, excluding those estimates derived from OTM options with zero total trading volume. The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line shows the spread between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	0.03	-0.13** (-4.63)	1.09**	0.29**	-0.12**	-0.04	0.92	109
2	0.12	-0.06* (-2.09)	1.19**	0.35**	-0.19**	-0.04	0.93	109
3	0.13	-0.05 (-1.70)	1.25**	0.50**	-0.23**	-0.05*	0.92	109
4	0.20	0.01 (0.18)	1.33**	0.61**	-0.30**	-0.06*	0.91	109
5 (Highest RNS)	0.33*	0.13** (3.03)	1.38**	0.75**	-0.37**	-0.16**	0.88	109
Spread (5-1)	0.30**	0.26**	0.29**	0.46**	-0.24**	-0.12*	0.36	
t(5-1)	(4.25)	(4.80)	(11.24)	(7.62)	(-4.20)	(-2.29)		

Table 1.A4: Short Horizon RNS-sorted Weekly Quintile Portfolio Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A). The sample ranges from January 1996 to June 2014 and contains only stocks whose RNS horizon is less or equal to 95 days. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line reports the spread between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	-0.01	-0.18**	1.18**	0.42*	-0.15*	-0.04	0.88	71
		(-4.58)						
2	0.11	-0.07	1.26**	0.41**	-0.26**	-0.03	0.90	70
		(-1.73)						
3	0.14	-0.04	1.29**	0.52**	-0.31**	-0.04	0.89	70
		(-1.24)						
4	0.21	0.02	1.37**	0.61**	-0.36**	-0.04	0.98	70
		(0.41)						
5 (Highest RNS)	0.30*	0.10*	1.38**	0.68**	-0.41**	-0.05	0.85	71
		(2.27)						
Spread (5-1)	0.27**	0.29**	0.20**	0.27**	-0.26**	-0.01	0.16	
t(5-1)	(4.34)	(4.80)						

Table 1.A5: Non-Parametric RNS-sorted Quintile Portfolios

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Non-Parametric Risk-Neutral Skewness (NPRNS) estimates. NPRNS is defined as the difference between the 30-day implied volatilities of OTM calls (deltas=0.20 and 0.25) and OTM puts (deltas=-0.20 and -0.25). The sample period is January 1996–June 2014. Every Wednesday, at market close, stocks are sorted in ascending order according to their NPRNS values and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate during the examined period. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. We also report portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model as well as its adjusted R^2 (R^2 adj.). N denotes the average number of stocks in each portfolio. The pre-last line shows the spread between the portfolio with the highest NPRNS stocks and the portfolio with lowest NPRNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest NPRNS)	-0.02	-0.20**	1.42**	0.76**	-0.26**	-0.32**	0.90	134
		(-4.37)						
2	0.14	-0.04	1.29**	0.49**	-0.20**	-0.11**	0.93	133
		(-1.31)						
3	0.20*	0.01	1.17**	0.40**	-0.10**	-0.01	0.94	133
		(0.40)						
4	0.21*	0.04	1.08**	0.39**	-0.11**	0.04	0.94	133
		(1.88)						
5 (Highest NPRNS)	0.27*	0.09**	1.13**	0.57**	-0.21**	0.04	0.90	134
		(2.64)						
Spread (5-1)	0.29**	0.29**	-0.29**	-0.19**	0.05	0.36**	0.44	
t(5-1)	(4.34)	(5.28)	(-9.03)	(3.76)	(0.79)	(7.25)		

Table 1.A6: Value Weighted RNS-sorted Weekly Quintile Portfolio Sorts

This Table reports the weekly post-ranking performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A). The sample ranges from January 1996 to June 2014 and contains only stocks whose RNS horizon is less or equal to 95 days. Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values and they are assigned to quintile portfolios. The corresponding value-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line reports the spread between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	0.08	-0.09**	1.07**	0.25**	-0.15**	0.05	0.92	134
		(-3.26)						
2	0.16	-0.02	1.14**	0.30**	-0.16**	0.07**	0.94	133
		(-0.63)						
3	0.18	-0.01	1.20**	0.44**	-0.22**	0.06**	0.93	133
		(-0.51)						
4	0.26*	0.06	1.26**	0.52**	-0.25**	0.07**	0.91	133
		(1.83)						
5 (Highest RNS)	0.34**	0.13**	1.28**	0.66**	-0.26**	0.04	0.89	134
		(3.68)						
Spread (5-1)	0.26**	0.22**	0.22**	0.41**	-0.11**	-0.01	0.16	
t(5-1)	(4.71)	(5.10)						

Table 1.A7: RNS and ΔRNS-sorted Daily Quintile Portfolio Sorts

This Table reports the daily post-ranking performance of quintile stock portfolios constructed on the basis of their Risk-Neutral Skewness (RNS) estimates (Panel A), and the change in their RNS (ΔRNS) estimates relative to previous trading day (Panel B). The sample period is January 1996–June 2014. Each trading day, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following trading day (i.e., post-ranking daily returns). Ex Ret denotes the average daily portfolio return in excess of the risk-free rate. α_{FFC} denotes the daily portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line in Panel A (Panel B) reports the spread between the portfolio with the highest RNS (ΔRNS) stocks and the portfolio with lowest RNS (ΔRNS) stocks. Panel C reports the corresponding results for two bivariate stock portfolios, constructed as the intersections of the lowest (highest) RNS and the lowest (highest) ΔRNS independently-sorted quintiles. The pre-last line in Panel C reports the spread between these two portfolios. t-values calculated using Newey-West standard errors with 9 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: RNS-sorted Quintile Portfolios								
Quintiles	Ex Ret	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}	R^2 adj.	N
1 (Lowest RNS)	-0.04	-0.07** (-11.96)	1.04**	0.28**	-0.05*	-0.05**	0.93	134
2	-0.01	-0.04** (-7.38)	1.11**	0.40**	-0.12**	-0.05**	0.94	133
3	0.01	-0.03** (-4.23)	1.18**	0.54**	-0.19**	-0.06**	0.93	133
4	0.06*	0.02* (2.16)	1.25**	0.63**	-0.25**	-0.06**	0.92	133
5 (Highest RNS)	0.14**	0.10** (10.25)	1.31**	0.76**	-0.29**	-0.12**	0.89	134
Spread (5-1)	0.18**	0.17**	0.27**	0.49**	-0.23**	-0.07*	0.36	
t(5-1)	(12.18)	(14.00)	(15.93)	(12.97)	(-6.50)	(-2.18)		

Panel B: ΔRNS-sorted Quintile Portfolios								
1 (Lowest ΔRNS)	-0.06*	-0.10** (-13.73)	1.18**	0.54**	-0.22**	-0.08**	0.92	125
2	-0.01	-0.05** (-7.04)	1.17**	0.52**	-0.16**	-0.06**	0.93	124
3	0.03	-0.01 (-1.04)	1.17**	0.51**	-0.16**	-0.06**	0.93	124
4	0.07**	0.03** (5.22)	1.19**	0.51**	-0.18**	-0.05**	0.93	124
5 (Highest ΔRNS)	0.13**	0.09** (11.49)	1.21**	0.49**	-0.24**	-0.06**	0.91	124
Spread (5-1)	0.19**	0.19**	0.04**	-0.05*	-0.02	0.01	0.01	
t(5-1)	(19.48)	(19.30)	(2.85)	(-2.36)	(0.88)	(0.98)		

Table 1.A5: (Continued)

Panel C: Bivariate RNS & ΔRNS Independently-sorted Portfolios								
RNS 1 & ΔRNS 1	-0.09**	-0.13** (-14.31)	1.07**	0.35**	-0.10**	-0.06**	0.85	42
RNS 5 & ΔRNS 5	0.22**	0.18** (13.95)	1.31**	0.66**	-0.32**	-0.09**	0.82	43
Spread (5&5- 1&1)	0.31**	0.31**	0.24**	0.31**	-0.22**	-0.03	0.16	
t(5&5- 1&1)	(18.19)	(18.62)	(10.40)	(7.94)	(-5.15)	(-1.11)		

Table 1.A8: Bivariate Portfolio Sorts: ΔRNS and Stock Mispricing

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day and each of the two stock mispricing proxies used. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016) in Panel A, and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016) in Panel B. A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their ΔRNS estimates and they are assigned to tercile portfolios. Within each ΔRNS tercile portfolio, we further sort stocks according to their Wednesday DOTS values (Panel A.1) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their ΔRNS estimates and their Wednesday DOTS values (Panel A.2) or their end-of-month, prior to the sorting Wednesday, MISP values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these ΔRNS- and stock mispricing-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: DOTS

Panel A.1: Conditional Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)	Panel A.2: Independent Portfolios	DOTS Lowest	DOTS Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	0.03	-0.34**	0.36**	ΔRNS 1 (Lowest)	0.04	-0.27**	0.31**
	(0.75)	(-6.97)	(7.11)		(0.83)	(-6.65)	(6.06)
					[40]	[94]	
ΔRNS 3 (Highest)	0.21**	-0.13**	0.34**	ΔRNS 3 (Highest)	0.18**	-0.20**	0.37**
	(4.82)	(-3.47)	(6.73)		(4.85)	(-4.05)	(6.84)
					[98]	[44]	
Spread (3-1)	0.19**	0.21**		Spread (3-1)	0.14**	0.07	
	(3.93)	(4.43)			(2.85)	(1.43)	

Panel B: MISP

Panel B.1: Conditional Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)	Panel B.2: Independent Portfolios	MISP Lowest	MISP Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	-0.04	-0.24**	0.20**	ΔRNS 1 (Lowest)	-0.05	-0.24**	0.19**
	(-1.13)	(-4.91)	(3.45)		(-1.34)	(-4.98)	(3.36)
					[64]	[65]	
ΔRNS 3 (Highest)	0.13**	-0.00	0.13*	ΔRNS 3 (Highest)	0.13**	-0.01	0.14*
	(3.89)	(-0.10)	(2.23)		(4.20)	(-0.12)	(2.37)
					[64]	[65]	
Spread (3-1)	0.17**	0.24**		Spread (3-1)	0.18**	0.23**	
	(4.27)	(4.32)			(4.51)	(4.46)	

Table 1.A9: Bivariate Portfolio Sorts: ΔRNS and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of bivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010) in Panel A, and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006) in Panel B. A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. For the conditional portfolios (Panels A.1 and B.1), at market close every Wednesday, stocks are sorted in ascending order according to their ΔRNS estimates and they are assigned to tercile portfolios. Within each ΔRNS tercile portfolio, we further sort stocks according to their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.1) or ESF values (Panel B.1), and construct again tercile portfolios. For the independent portfolios (Panels A.2 and B.2), at market close every Wednesday, stocks are independently sorted in ascending order according to their ΔRNS estimates and their end-of-month, prior to the sorting Wednesday, EIS^P (Panel A.2) or ESF values (Panel B.2), and they are assigned to tercile portfolios. The intersections of these ΔRNS- and stock downside risk-sorted terciles yield the independent portfolios. The average number of stocks per portfolio is reported in square brackets. In both approaches, equally-weighted returns of the corresponding portfolios are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: EIS^P

Panel A.1: Conditional Portfolios				Panel A.2: Independent Portfolios			
	EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)		EIS^P Lowest	EIS^P Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	-0.01	-0.20**	0.19**	ΔRNS 1 (Lowest)	0.00	-0.20**	0.21**
	(-0.19)	(-4.18)	(3.32)		(0.11)	(-4.35)	(3.58)
					[53]	[54]	
ΔRNS 3 (Highest)	0.14**	0.05	0.10	ΔRNS 3 (Highest)	0.15**	0.06	0.10
	(3.64)	(1.18)	(1.74)		(3.79)	(1.40)	(1.74)
					[52]	[54]	
Spread (3-1)	0.15**	0.25**		Spread (3-1)	0.15**	0.26**	
	(3.70)	(4.74)			(3.46)	(4.88)	

Panel B: ESF

Panel B.1: Conditional Portfolios				Panel B.2: Independent Portfolios			
	ESF Lowest	ESF Highest	Spread (Lowest-Highest)		ESF Lowest	ESF Highest	Spread (Lowest-Highest)
ΔRNS 1 (Lowest)	0.01	-0.21**	0.21**	ΔRNS 1 (Lowest)	-0.00	-0.22**	0.21**
	(0.17)	(-3.77)	(4.08)		(-0.10)	(-4.09)	(4.21)
					[62]	[52]	
ΔRNS 3 (Highest)	0.10*	0.01	0.08	ΔRNS 3 (Highest)	0.09*	-0.01	0.11*
	(2.47)	(0.26)	(1.66)		(2.40)	(-0.28)	(2.19)
					[62]	[52]	
Spread (3-1)	0.09**	0.22**		Spread (3-1)	0.10**	0.21**	
	(2.70)	(4.16)			(2.90)	(3.95)	

Table 1.A10: Trivariate Independent Portfolio Sorts: ΔRNS, Stock Mispricing and Downside Risk

This Table reports the weekly post-ranking risk-adjusted performance of trivariate stock portfolios constructed on the basis of the change in their Risk-Neutral Skewness (ΔRNS) estimates relative to the previous trading day, each of the two proxies used for stock mispricing, and each of the two proxies used for stock downside risk. The sample period is January 1996–June 2014. We use the following two proxies for stock mispricing: i) the distance between the actual stock price and the option-implied stock value (DOTS) of Goncalves-Pinto et al. (2016), and ii) the composite mispricing rank (MISP) of Stambaugh and Yuan (2016). A low (high) value of DOTS or MISP indicates that the stock is relatively underpriced (overpriced). We use the following two proxies for stock downside risk: i) the expected idiosyncratic skewness (EIS^P) of daily stock returns under the physical measure of Boyer et al. (2010), and ii) the estimated stock shorting fee (ESF) of Boehme et al. (2006). A low (high) value of EIS^P or ESF indicates that the stock is exposed to greater (lower) downside risk. Every Wednesday, at market close, stocks are independently sorted in ascending order according to: 1) their ΔRNS estimates, 2) their Wednesday DOTS values or their end-of-month, prior to the sorting Wednesday, MISP values, and 3) their end-of-month, prior to the sorting Wednesday, EIS^P or ESF values, and they are classified for each sorting criterion as Low (L) or High (H) relative to the corresponding median value. The intersections of these three classifications yield 8 portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). We report weekly portfolio alphas (in percentages) estimated from the Fama-French-Carhart (FFC) 4-factor model. The average number of stocks per portfolio is reported in square brackets. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

	Stock Mispricing Proxy	DOTS		MISP	
	Downside Risk Proxy	EIS^P	ESF	EIS^P	ESF
P1	ΔRNS Low & DOTS/ MISP Low & EIS^P/ ESF Low	0.15** (3.61) [46]	0.06 (1.57) [55]	0.06 (1.68) [65]	0.03 (0.82) [76]
P2	ΔRNS Low & DOTS/ MISP Low & EIS^P/ ESF High	-0.08 (-1.81) [44]	-0.04 (-0.76) [42]	-0.05 (-1.30) [52]	-0.07 (-1.40) [45]
P3	ΔRNS Low & DOTS/ MISP High & EIS^P/ ESF Low	-0.08* (-1.97) [69]	-0.05 (-1.57) [77]	-0.03 (-0.56) [52]	-0.04 (-1.05) [53]
P4	ΔRNS Low & DOTS/ MISP High & EIS^P/ ESF High	-0.23** (-6.46) [72]	-0.24** (-5.18) [74]	-0.25** (-5.75) [64]	-0.18** (-3.77) [68]
P5	ΔRNS High & DOTS/ MISP Low & EIS^P/ ESF Low	0.18** (4.54) [71]	0.15** (4.15) [84]	0.12** (3.48) [64]	0.13** (3.58) [76]
P6	ΔRNS High & DOTS/ MISP Low & EIS^P/ ESF High	0.12** (3.39) [70]	0.09* (2.02) [67]	0.10** (3.11) [53]	0.03 (0.55) [45]
P7	ΔRNS High & DOTS/ MISP High & EIS^P/ ESF Low	-0.06 (-1.53) [44]	-0.00 (-0.12) [48]	0.08 (1.80) [53]	0.08 (1.73) [53]
P8	ΔRNS High & DOTS/ MISP High & EIS^P/ ESF High	-0.13** (-2.93) [45]	-0.18** (-3.53) [49]	0.01 (0.12) [64]	0.00 (0.01) [67]

Table 1.A11: RNS-sorted Portfolios: Decomposing First Post-Ranking Day Returns in Subperiods

This Table reports a decomposition of the first post-ranking trading day performance of quintile stock portfolios constructed every Wednesday on the basis of their Risk-Neutral Skewness (RNS) estimates for the sample period January 1996-February 2008 (Panel A) and April 2008-June 2014 (Panel B). Every Wednesday, at market close, stocks are sorted in ascending order according to their RNS values (Panel A) or their ΔRNS values (Panel B), and they are assigned to quintile portfolios. The corresponding equally-weighted portfolio returns are computed at market close of the following Wednesday (i.e., post-ranking weekly returns). Ex Ret denotes the average weekly portfolio return in excess of the risk-free rate. α_{FFC} denotes the weekly portfolio alpha estimated from the Fama-French-Carhart (FFC) 4-factor model. Excess returns and alphas are expressed in percentages. Portfolio loadings (β's) with respect to the market (MKT), size (SMB), value (HML) and momentum (MOM) factors estimated from the FFC model and its adjusted R^2 (R^2 adj.) are also reported. N denotes the average number of stocks per portfolio. The pre-last line reports the spread between the portfolio with the highest RNS stocks and the portfolio with lowest RNS stocks. t-values calculated using Newey-West standard errors with 7 lags are provided in parentheses. **, and * indicate statistical significance at the 1%, and 5% level, respectively.

Panel A: January 1996 – February 2008

Overnight Performance			Intraday Performance		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest RNS)	-0.05	-0.06**	1 (Lowest RNS)	0.03	-0.01
		(-5.36)			(-0.68)
2	-0.02	-0.03**	2	0.02	-0.03
		(-3.19)			(-1.90)
3	0.02	0.00	3	0.02	-0.03
		(0.48)			(-2.04)
4	0.09*	0.06**	4	0.03	-0.03
		(5.23)			(-1.43)
5 (Highest RNS)	0.20**	0.16**	5 (Highest RNS)	0.01	-0.05**
		(9.93)			(-2.33)
Spread (5-1)	0.25**	0.22**	Spread (5-1)	-0.02	-0.02
t(5-1)	(10.67)	(10.61)	t(5-1)	(-0.73)	(-1.82)

Panel B: April 2008 – June 2014

Overnight Performance			Intraday Performance		
Quintiles	Ex Ret	α_{FFC}	Quintiles	Ret	α_{FFC}
1 (Lowest ΔRNS)	0.03	-0.04**	1 (Lowest ΔRNS)	0.03	-0.01
		(-5.47)			(-0.30)
2	0.05	-0.02**	2	0.06	-0.02
		(-3.91)			(-1.30)
3	0.05	-0.02**	3	0.06	-0.01
		(-4.06)			(-0.92)
4	0.08	-0.00	4	0.06	-0.01
		(-0.36)			(-0.41)
5 (Highest ΔRNS)	0.11**	0.05**	5 (Highest ΔRNS)	0.01	-0.04
		(4.01)			(-1.67)
Spread (5-1)	0.11**	0.09**	Spread (5-1)	0.02	0.03
t(5-1)	(5.58)	(5.37)	t(5-1)	(1.53)	(1.56)

Chapter 2

Manifestations of Political Uncertainty around US Presidential Elections: Cross-Sectional Evidence from the Option Market

2.1 Introduction

Democratic political processes can exert a significant impact on financial markets (see Bernhard and Leblang, 2006; Fowler, 2006; Snowberg, Wolfers, and Zitzewitz, 2007, and references therein). In fact, there is a growing interest in understanding how market participants react to episodes of political uncertainty, primarily around elections, and how this type of uncertainty affects firm operations, value, and risk (see, *inter alia* Pantzalis, Stangeland, and Turtle, 2000; Li and Born, 2006; Bialkowski, Gottschalk, and Wisniewski, 2008; Boutchkova, Doshi, Durnev, and Molchanov, 2012; Julio and Yook, 2012; Durnev, 2012; Goodell and Vahamaa, 2013; Kelly, Pastor, and Veronesi, 2016; Colak, Durnev, and Qian, 2017; Jens, 2017; Chan and Marsh, 2018; Brogaard, Dai, Ngo, and Zhang, 2019). Though political uncertainty is a recurring theme in the media and the public debate, as Kelly et al. (2016, p. 2417) state: "our understanding of its effects on the economy and financial markets is only beginning to emerge". To this end, our study provides comprehensive evidence with respect to the manifestations of political uncertainty around US presidential elections, both at the aggregate level and across firms with different political characteristics. In particular, our study utilizes information from the option market to examine whether political uncertainty, caused by the occurrence of US presidential elections, leads to an increase in stock price and tail risk as well as the equity premium, and whether it gives rise to an increased trading activity and dispersion in investor beliefs. Moreover, we test the conjecture that these effects should be more pronounced for firms that are particularly exposed to various dimensions of political risk.

US presidential elections provide a unique setting to identify the effects of political uncertainty because they take place on regular, fixed dates, which are publicly known well in advance. Hence, their regular occurrence constitutes an exogenous episode of political uncertainty, the timing of which is independent of the prevailing macroeconomic and financial conditions or corporate political activity and characteristics, sidestepping concerns related to reverse causality or omitted variables. In contrast, other well-studied political events, such as elections in other countries, referenda, and international summits, may be the result, rather than the cause, of developments in financial markets and the macroeconomy, or corporate political activity. The presidential election is the most important global political event, it is extensively covered by the media, and it is closely followed by market participants because it could result in major policy shifts. Hence, it is highly unlikely that, during the narrow period around the presidential election, asset prices may alternatively reflect a confounding event.

Interestingly, US presidential elections provide an additional feature that we exploit in our empirical analysis. Though the uncertainty regarding the outcome is immediately resolved on the election night (with the infamous exception of the 2000 *Gore vs. Bush* contest), the uncertainty regarding the composition, orientation, and policies of the new administration, in conjunction with the potentially new majorities in the Senate and the House of Representatives, is not immediately resolved. As a result, the effects of uncertainty regarding future government policy, as in Pastor and Veronesi (2013), may actually persist during the transition period between the presidential election in November and the inauguration in January.

Similar to Kelly et al. (2016), we conduct our empirical analysis using information from the equity option market. Option-based information enables our inference for a number of reasons. Options come with different strike prices, allowing us to capture different dimensions of firm risk, even if these do not subsequently materialize. In particular, we capture equity price risk via the implied volatility of at-the-money options, and downside tail risk (i.e., the risk of a large stock price drop) via the expensiveness of deep out-of-the-money (OTM) puts relative to at-the-money options. This feature also allows us to compute a measure of expected stock return that has been recently proposed by Martin and Wagner (2019). Moreover, examining the trading activity of options with different levels of moneyness, we can make inferences regarding the underlying trading motives of market participants and the degree of dispersion of their beliefs.

In addition, short-maturity options can help us isolate the effects of political uncertainty due to the presidential election. In particular, comparing the information embedded in options whose life spans the presidential election with the corresponding information embedded in similar options that expire before the election, we can attribute any differences to the uncertainty caused by the election. Furthermore, the option-based variables we utilize are typically available on a daily basis, enabling identification; we can measure the effects of political uncertainty relying on very short windows around the presidential election, instead of using long estimation windows that could be contaminated with other market-wide or firm-level confounding events.

An innovative feature of our study is that it examines the differential effects of political uncertainty across firms with different political characteristics.[1] We focus on the following four dimensions. First, we consider firm sensitivity to economic policy uncertainty, as proxied by the index of Baker, Bloom, and Davis (2016). Policy uncertainty can have a real effect on corporate policies (Gulen and Ion, 2016, see, for example), and more sensitive firms may command a higher risk premium (Brogaard and Detzel, 2015). Akey and Lewellen (2017) argue that sensitivity to policy uncertainty can also motivate corporate political activity, such as lobbying and donations to politicians. In fact, the presidential election constitutes a primary source of uncertainty regarding future government policy, in the spirit of the model of Pastor and Veronesi (2013).

Second, we examine the effect of stock return exposure to the party affiliation of the US President. Santa-Clara and Valkanov (2003) document systematic patterns in stock returns depending on the presidential party, whereas Addoum and Kumar (2016) argue that certain industries can be favorably or adversely exposed to a Republican or Democrat administration, and that investors attempt to exploit these patterns. Naturally, there is a high degree of uncertainty regarding the "winners" and "losers" of each presidential election, so the effects we examine may be more pronounced during this period for firms whose stock returns are politically exposed in the first place. For example, firms that are favourably exposed to the incumbent presidential party are expected to feature a larger increase in their level of risk and their equity premium, as a result of the political uncertainty triggered by the presidential election.

[1] It should be noted that these characteristics are measured well before the election period, sidestepping any endogeneity concerns.

The third feature we study is the political alignment of firms with the presidential party on the basis of their headquarters' state. Kim, Pantzalis, and Chul Park (2012) show that geographical proximity to the political power of the ruling party has a pervasive effect on stock returns, possibly because it reflects exposure to policy risk. The location of a firm's headquarters can also lead to an indirect form of connectedness with politicians, who may have the incentives and power to favor "local" firms (see Faccio and Parsley, 2009). Since presidential elections are expected to cause shifts in the political map, the effects of political uncertainty during this period may be exacerbated for firms that are strongly aligned with the incumbent or contender party.

Last but not least, we examine the effect of direct political connectedness through contributions to federal candidates' election campaigns (see Ansolabehere, De Figueiredo, and Snyder, 2003, for an introduction) Campaign contributions are regarded as a form of "political capital" to the benefit of shareholders via rent seeking or to hedge background risks, such as sensitivity to policy uncertainty. More generally, they are viewed as a proxy for engaging in the political process.[2] Cooper, Gulen, and Ovtchinnikov (2010) document a strong positive correlation between campaign contributions and future stock returns, but remain agnostic on whether this finding indicates mispricing or compensation for exposure to political risk. Akey (2015) estimates large positive abnormal returns for firms that have donated "hard money" to marginally winning candidates relative to losing ones. More recently, Akey and Lewellen (2017) show that firms connected with marginally winning candidates exhibit an improvement in their operating performance and a reduction in their risk-taking. During presidential elections, which coincide with elections for the House and (approximately a third of) Senate seats,

[2]Beyond campaign contributions, there is a growing literature on the effects of alternative forms of direct political connectedness (see, *inter alia* Faccio, 2006; Faccio, Masulis, and Mcconnell, 2006; Goldman, Rocholl, and So, 2009; Hill, Kelly, Lockhart, and Van Ness, 2013; Borisov, Goldman, and Gupta, 2016; Acemoglu, Johnson, Kermani, Kwak, and Mitton, 2016, and references therein).

new connections are being established and existing connections can be lost, potentially aggravating the effect of political uncertainty.

Our empirical analysis yields a number of interesting results. We estimate a significant average increase in price and tail risk as well as the expected return across firms, regardless of their political features, in the narrow period prior to the presidential election, relative to a carefully defined benchmark period. In particular, the annualized implied volatility of at-the-money options exhibits an average increase of approximately 5.5%. In addition, the wedge between the annualized implied volatilities of deep OTM puts and at-the-money options further increases by more than 0.8%. This increase in stock price and tail risk is associated with an average increase in the expected return on equity of approximately 40 basis points (bps) per month. Interestingly, we also document that the effects of political uncertainty persist in the narrow period after the presidential election. Though the magnitude of these increases is somewhat smaller relative to the corresponding increases just before the election, they remain strongly significant in both economic and statistical terms. This finding is consistent with a short delay in the resolution of uncertainty regarding the new administration's policy priorities and key appointments, even though the election outcome is known.

Even more interestingly, we find significant differential effects associated with firms' political characteristics. Specifically, in the period prior to the election, we report a large additional increase in the price and tail risk as well as the expected return for firms that are sensitive to policy uncertainty. We estimate a differential increase of approximately 6.8% in the implied volatility of at-the-money options, an additional increase of 1% in the difference between the implied volatilities of OTM puts and at-the-money options, and a further increase of more than 90 bps per month in the expected return of sensitive firms. As a result, the effects of political uncertainty on sensitive firms are estimated to be more than twice as large as the corresponding effects on non-sensitive firms. Moreover, these differential effects for sensitive firms persist in the first few days after the election.

We also find a significant differential increase in the risk and expected return of firms that are exposed (either favorably or adversely) to the presidential party. Identifying the party to which firms are exposed, we find that the differential effects prior to the election are stronger for firms that are favorably exposed to the incumbent party. This finding is consistent with the conjecture that these firms have more to lose from a potential change in the presidential party. We report significant differential effects in the narrow period after the election too. In particular, we estimate a large differential increase in the expensiveness of at-the-money options as well as in the expected return of firms which are exposed to the party that has just lost the election. To the contrary, we find no such effects for firms that are exposed to the winning party.

With respect to geographical political alignment, we report substantial differential increases just before the election in the price and tail risk as well as the premium commanded by firms that are aligned with the presidential party. There is no such effect for firms that are aligned with the contender party. In the few days after the election, we estimate an additional increase in the expensiveness of at-the-money options and the expected return for firms which are aligned with the party that has just lost the election.

The differential effects of political uncertainty are much weaker for connected firms. In fact, we only find a significant additional increase in the relative expensiveness of their OTM puts prior to the presidential election, but this does not translate into a higher equity premium. Moreover, examining the interaction between sensitivity to policy uncertainty and political connectedness, we find no evidence that the latter acts as a mitigating factor with respect to the effect of political uncertainty. Similarly, we find that political hedging, in the form of contributing to candidates of both parties in a balanced way, does not lead to a relative reduction in the equity risk or premium in the run up to the election.

These findings are robust to alternative definitions of the benchmark, election, and post-election periods, different definitions of firm political characteristics, and the use of a subsample with big- and mid-cap firms only. Moreover, we conduct placebo tests to ensure that the magnitude of the estimated effects can be genuinely attributed to the political uncertainty surrounding the actual presidential election days, and they could not be spuriously caused by "luck" or alternative combinations of other, non-election events.

We also derive interesting conclusions with respect to option trading activity and the dispersion of investor beliefs around presidential elections. In particular, we find a significant overall increase in option trading volume prior to the election day, which is resembled by corresponding increases in the trading volume of both OTM calls and OTM puts. Hence, the importance of the option market as a trading venue increases prior to presidential elections. However, we report no consistent evidence that corporate political characteristics exert significant differential effects on option trading volume during this period. Moreover, we find that political uncertainty substantially increases the dispersion of investor beliefs with respect to future price shifts around presidential elections. Interestingly, we also show that firm political characteristics can render these beliefs even more disperse. This is particularly true prior to the election for firms that are sensitive to policy uncertainty as well as for firms that are exposed to or are geographically politically aligned with the presidential party.

Our study is related to a number of prior studies. Similar to Kelly et al. (2016), we examine the pricing of political uncertainty using information from the option market. However, we focus on US presidential elections, whose exogenous and fixed timing justifies the attribution of the estimated effects to the political uncertainty caused by the electoral event. More interestingly, we utilize a large cross-section of firms, rather than the aggregate market portfolio, which allows us to examine the differential effects of this type of uncertainty across firms with different political characteristics. We further contribute to the literature by providing comprehensive evidence on the effects of political uncertainty on expected equity returns, option trading activity, and the dispersion of investor beliefs.

Our findings are in line with the conclusions of Boutchkova et al. (2012) regarding the increase in stock return volatility in election years. They are also consistent with the global increase in volatility and the price of risk in the six-month period prior to US federal elections, which is reported in Brogaard et al. (2019). However, our empirical design and the use of option-implied information allow us to examine very narrow periods before and after the presidential election, instead of relying on stock return volatility estimated over long windows. These methodological innovations also enable us to provide a cleaner identification of the effects of political uncertainty around elections on equity tail risk, expected return, option trading activity, and the dispersion of investor beliefs, not only volatility. Moreover, different from Boutchkova et al. (2012), we estimate cross-sectional differential effects on the basis of firm-level political features, rather than operational characteristics at the industry level.

Similar to Akey and Lewellen (2017), we also examine cross-sectional differential effects around election events on the basis of corporate political characteristics. However, our focus is on the pricing of political uncertainty and its implications for equity risk, premia, trading activity, and the dispersion of investor beliefs, rather than the causal effect of election shocks on corporate risk-taking and operating performance. We further contribute to the literature that examines the relationship between corporate political characteristics and stock returns. Our results provide support to the arguments of Brogaard and Detzel (2015) and Kim et al. (2012) that sensitivity to economic policy uncertainty and geographical political alignment with the presidential party, respectively, can be regarded as sources of risk. The same argument holds true particularly for firms whose stock returns are favourably exposed to the presidential party. To the contrary, our results do not support the conjecture that political connectedness can be regarded as a missing risk factor to explain the findings of Cooper et al. (2010).

The rest of the study is organised as follows. Section 2 outlines our data sources and the construction of the variables used in the empirical analysis. Section 3 describes in detail the empirical design of the study. Section 4 presents our benchmark results regarding the effects of political uncertainty on firm risk and expected return, whereas Section 5 contains a number of robustness checks. Section 6 examines the effects on option trading activity and the dispersion of investor beliefs, and Section 7 concludes.

2.2 Data sources and variables

2.2.1 Data sources

We construct a number of variables for US common stocks (shrcd 10 and 11) listed on NYSE, NYSE American, and NASDAQ (exchcd 1, 2, 3, 31, 32, 33) during the period 1996-2016. We use monthly and daily stock returns as well as daily stock trading volume from CRSP. Option data are sourced from OptionMetrics. We utilize the 30-day Volatility Surface file to compute the price-related option variables. We also use information from equity options to compute the trading activity-related option variables. Information on the state in which corporate headquarters are located as well as S&P 500 and S&P Mid-Cap 400 stock constituent lists are extracted from COMPUSTAT. We obtain data on campaign contributions to Presidential, Senate, and House candidates from the US Federal Election Commission (FEC) database.[3] Election results are sourced from the MIT Election Lab.[4] We also use the Economic Policy Uncertainty (EPU) Index of Baker et al. (2016), the Political Alignment Index (PAI) of Kim et al. (2012), the Macroeconomic Uncertainty Index (MUI) of Jurado, Ludvigson, and Ng (2015), and the S&P 500 VIX.[5]

2.2.2 Option-based variables

2.2.2.1 Price risk, tail risk, and expected stock return

Similar to An et al. (2014) and Bali et al. (2017), we use the 30-day Volatility Surface file from OptionMetrics to compute three price-related option variables (*ATM*, *LSKEW*, and *OIEXRET*). This file contains implied volatilities for standardized equity options with 30-day expiry for a grid of the delta space, which is often used as a measure of option moneyness. The implied volatility surface provides a standardized way of measuring the expensiveness of equity options with different strikes and maturities.[6]

[3]The database with the campaign contributions can be found at: https://www.fec.gov/data.

[4]The databases containing the election results can be found at: https://electionlab.mit.edu/data.

[5]We are grateful to Chris Pantzalis for sharing the PAI data. The EPU Index can be found at www.policyuncertainty.com. MUI is sourced from Sydney Ludvigson's website: www.sydneyludvigson.com/data-and-appendixes.

[6]Firm-level equity options are typically American-style options. OptionMetrics compute the interpolated volatility surface separately for puts and calls using a kernel smoothing technique. The underlying implied volatilities of equity options with various strikes and maturities are computed using an adapted Cox-Ross-Rubinstein binomial tree model that accounts for the early exercise premium of the American-style options and dividends that firms are expected to pay during the lives of the options.

ATM measures stock price risk and it is computed as the average implied volatility of at-the-money call and put options:

$$\begin{aligned} ATM &= (ATM_{CALL} + ATM_{PUT})/2 \\ &= \left(CIV_{50} + CIV_{55} + PIV_{-45} + PIV_{-50}\right)/4, \end{aligned} \tag{2.1}$$

where CIV_{50} (CIV_{55}) is the implied volatility of the 0.5 (0.55) delta call and PIV_{-50} (PIV_{-45}) is the implied volatility of the -0.5 (-0.45) delta put.[7] A higher ATM value indicates an increase in stock price risk, which renders at-the-money options more expensive.[8]

$LSKEW$ captures stock tail risk and it is computed as the difference between the implied volatility of relatively deep OTM puts and ATM:

$$LSKEW = DOTM_{PUT} - ATM = \left(PIV_{-20} + PIV_{-25}\right)/2 - ATM, \tag{2.2}$$

where PIV_{-20} (PIV_{-25}) is the implied volatility of the -0.2 (-0.25) delta put. By measuring the expensiveness of relatively deep OTM puts, which are typically used by investors for protection against large stock price drops, relative to the expensiveness of at-the-money options, $LSKEW$ identifies stock tail risk on top of the overall price risk that is captured by ATM. A higher $LSKEW$ value indicates an increase in stock tail risk, i.e., an increase in the risk of a large stock price drop.[9] $LSKEW$ is very similar to the SKEW measure of Xing et al. (2010) and

[7] We opt for the average implied volatility using both calls and puts, instead of calls or puts only, to average out any discrepancies arising due to deviations from put-call parity in American-style options. In addition, since at-the-money calls (puts) do not exactly correspond to a 0.5 (-0.5) delta, we use the average implied volatility of 0.5 & 0.55 delta calls (similarly, -0.5 & -0.45 delta puts) since the exact at-the-money point most often lies between these two delta points. Nevertheless, our empirical results are very similar if we compute ATM using 0.5 (-0.5) delta calls (puts), as in An et al. (2014).

[8] To be precise, an increase in ATM may actually reflect an increase in volatility under the physical measure, or an increase in the price of volatility risk under the physical measure, or their combined effect. To keep the terminology simple, throughout the study we maintain the interpretation that ATM reflects the degree of stock price risk under the risk-neutral measure, acknowledging that both of the above mechanisms could be in play under the physical measure.

[9] Similar to the interpretation of ATM, we maintain the interpretation that $LSKEW$ captures the degree of stock tail risk under the risk-neutral measure, acknowledging that an increase in

reflects the left slope or steepness of the implied volatility curve.[10]

OIEXRET denotes the option-implied expected excess return of a stock, as defined by Martin and Wagner (2019). *OIEXRET* is a function of the market's risk-neutral variance as well as the stock's excess risk-neutral variance relative to the average stock, with the risk-neutral variances computed from OTM put and call prices. In particular, *OIEXRET* for stock i at time t is defined as:

$$OIEXRET_{i,t} = \frac{E_t\left(R_{i,t+1} - R_{f,t+1}\right)}{R_{f,t+1}} = SVIX_t^2 + \frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX}_t^2\right) + \alpha_i, \quad (2.3)$$

where $SVIX_t^2 = var^Q(R_{m,t+1}/R_{f,t+1})$, $SVIX_{i,t}^2 = var^Q(R_{i,t+1}/R_{f,t+1})$, $\overline{SVIX}_t^2 = \sum_i w_{i,t} SVIX_{i,t}^2$, $w_{i,t}$ is the market value weight of stock i, and α_i is a firm fixed effect.[11] To compute these risk-neutral variances, we follow the approach of Martin and Wagner (2019), utilizing implied option prices from the 30-day Volatility Surface file.[12]

2.2.2.2 Trading activity and dispersion of investor beliefs

We also construct a number of trading activity-related option variables. Consistent with the empirical design for our benchmark results, which is described in Section 3, we compute these variables using options with expiry between 16 and 60 days

LSKEW may actually reflect an increase in the probability of a large stock price drop under the physical measure, or an increase in the price of tail risk under the physical measure, or their combined effect.

[10]Kelly et al. (2016) measure tail risk by directly estimating the left slope of the implied volatility curve of equity index options, regressing the implied volatilities of OTM puts on their deltas. Hence, they require at least three OTM puts with the same maturity. However, this number of OTM puts with the same maturity is not typically available on a daily basis for a large cross-section of firms. Therefore, our measure of tail risk is based on the standardized implied volatility surface provided by OptionMetrics. Nevertheless, the two approaches are equivalent by construction.

[11]To be precise, we compute 30-day ahead expected excess stock returns up to a firm fixed effect. Our regression model specifications always include firm-by-election cycle fixed effects, enabling the correct interpretation of *OIEXRET*.

[12]To compute *OIEXRET* for a firm on a given day, we require all 26 delta points to be available at the Volatility Surface. Following Martin and Wagner (2019), we also filter out firm-day observations if $SVIX_{i,t}$ does not monotonically increase across horizons.

ahead. *TOTVOL* denotes the daily total trading volume across option contracts. *TOTOI* measures the daily total open interest across these option contracts. An increase in *TOTVOL* and *TOTOI* indicates an increase in trading activity in the option market. *TOTVOL-to-STOCKVOL* denotes the daily ratio of *TOTVOL* divided by the stock trading volume, measuring the trading activity in the option market relative to the corresponding activity in the stock market.

OTMPUTVOL stands for the daily total trading volume of OTM puts with moneyness $K/S < 0.95$. *OTMPUTVOL-to-TOTVOL* denotes the daily ratio of *OTMPUTVOL* divided by *TOTVOL*.[13] An increase in *OTMPUTVOL* is commonly thought to indicate an increase in the hedging demand by investors who seek protection against a large stock price drop, whereas an increase in *OTMPUTVOL-to-TOTVOL* captures this hedging activity after adjusting for a potential overall increase in option trading activity. Moreover, *OTMCALLVOL* measures the daily total trading volume of OTM calls with moneyness $K/S > 1.05$. An increase in *OTMCALLVOL* possibly indicates an increase in speculative demand by investors who seek to profit from a large stock price increase.

DISPOI measures the daily dispersion of options' open interest across levels of moneyness M_j. Given a range of strikes $K_j = 1, 2, ..., N$, *DISPOI* is defined as:

$$DISPOI = \sum_{j=1}^{N} \phi_j \mid M_j - \sum_{j=1}^{N} \phi_j M_j \mid , \tag{2.4}$$

where ϕ_j is the proportion of open interest for the option with strike K_j relative to all available strikes. We require at least 3 contracts with positive open interest to compute *DISPOI* on a given day.[14] An increase in *DISPOI* reflects an increase in the dispersion of investor beliefs regarding the future stock price.

[13] For this ratio, we add a very small positive number (0.01) to *TOTVOL*, to avoid zero values in the denominator.

[14] *DISPOI* is a slight modification of the corresponding measure introduced by Andreou, Kagkadis, Philip, and Taamouti (2018). Since we only utilize options with expiry between 16 and 60 days ahead, we use an open interest-weighted version of their measure to ensure that we can compute *DISPOI* for a sufficiently large cross-section at the daily frequency. Our empirical

In principle, the values of these trading activity-related variables are not comparable across firms and election cycles due to the potential firm and cycle fixed effects. Hence, we need to normalize the daily values of these trading activity-related variables in the sample period used for the empirical analysis. To this end, in each cycle, we express them as multiples (ratios) of the corresponding firm-level average daily value that is computed from January to June prior to the November presidential election, using a winsorization at the 99th percentile. In this way, we inherently neutralize both firm and election cycle effects, rendering the normalized values of these variables comparable in the cross-section and across cycles.

To ensure that the values of the option-based variables are reliable, we filter out firm-day observations when *TOTOI* for options with expiry between 16 and 60 days ahead is zero or when *ATM* cannot be computed from the Volatility Surface file. Moreover, we compute normalized versions of the trading activity-related variables only if at least two-thirds of their daily values during the averaging period (prior January to June) are non-zero, with the exception of *DISPOI* where this requirement is one-third of the values.

2.2.2.3 Summary statistics

Panel A of Table 2.1 reports the summary statistics for the option-based variables during the sample period used in our benchmark results, which corresponds to the union of the calendary day intervals: $[d-119, d-60]$, $[d-15, d-1]$, $[d+1, d+15]$, and $[d+61, d+120]$, where d is the US presidential election day from 1996 to 2016. The entire sample contains 936,959 firm-day observations for 3,956 unique firms (permnos) across the six election cycles. To reduce the impact of outliers, the price-related variables are winsorized at the 1st and 99th percentiles per election cycle, whereas the normalized trading activity-related variables are winsorized at

results are very similar if we instead use the trading volume-weighted version of this measure, as in Andreou et al. (2018), but they are based on a substantially smaller cross-section.

the 99th percentile. The median value of *ATM* is 44.12% p.a., whereas the median value of *LSKEW* is 3.82% p.a. The summary statistics show that firm-level implied volatilities exhibit substantial variation. Whereas OTM puts are typically more expensive than ATM options, as in the well-studied case of equity index options, *LSKEW* can also take negative values at the firm level. *OIEXRET* also exhibits substantial variation, with a median value of 49.5 bps per month. As expected, the values of the trading activity-related variables exhibit large variation too, and they are positively skewed.

2.2.3 Political variables

We construct a number of variables to capture corporate characteristics and activity in the following four political dimensions: *i*) sensitivity to economic policy uncertainty, *ii*) stock return exposure to the presidential party, *iii*) geographical political alignment with the presidential party, and *iv*) political connectedness via campaign contributions.

2.2.3.1 Sensitive firms

Following Akey and Lewellen (2017), we identify firms that are sensitive to economic policy uncertainty by estimating the following regression model, using excess monthly stock returns for each firm i:

$$r_{i,t} - r_{f,t} = \alpha_i + \delta_i EPU_t + \varepsilon_{i,t}, \tag{2.5}$$

where EPU_t is the Economic Policy Uncertainty Index of Baker et al. (2016).[15] In our benchmark results, we use a 36-month estimation window and we only

[15]The EPU Index is an aggregate time-series index based on the scaled frequency of articles in 10 leading US newspapers containing terms jointly related to uncertainty, the economy, and policy. See Baker et al. (2016) for details on the construction of this index.

include firms that have no missing returns during this period. *Sensitive* is a dummy variable that takes the value 1 for a firm if its coefficient estimate $\widehat{\delta_i}$ is significant at the 10% level, and 0 otherwise. A significant negative (positive) coefficient estimate $\widehat{\delta_i}$ indicates that the firm's stock return decreases (increases) when economic policy uncertainty increases. In Section 2.5, we perform a number of robustness tests using alternative definitions of *Sensitive* on the basis of a shorter estimation window as well as different specifications of model (2.5), which include the Macroeconomic Uncertainty Index of Jurado et al. (2015) or the S&P 500 VIX.

2.2.3.2 Exposed firms

We further identify firms whose stock returns are exposed to the party affiliation of the US President. In particular, following Addoum and Kumar (2016), we estimate the following regression model using excess monthly stock returns for each firm i:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{m,t} - r_{f,t}\right) + \theta_i RepubDummy_t + \varepsilon_{i,t}, \tag{2.6}$$

where $r_{m,t}$ is the market return and $RepubDummy_t$ is a dummy variable that is equal to 1 when the President is Republican, and 0 when the President is Democrat. This regression model is similar to the specification of Santa-Clara and Valkanov (2003). A positive (negative) coefficient estimate, $\widehat{\theta_i} > 0$ ($\widehat{\theta_i} < 0$), indicates that, ceteris paribus, the firm's stock yields a higher (lower) premium during Republican presidential terms.

Different from Addoum and Kumar (2016), who estimate this model using industry-level returns, we determine stock return exposure to the party affiliation of the President at the firm level. Moreover, since in our sample period no party held the presidency for more than two consecutive terms, we use a 10-year estimation window of monthly observations, and we only include firms with no missing returns.[16]

In our benchmark results, we set $RepubDummy_t$ equal to 1 from November after a Republican President is elected, and equal to 0 from November after a Democrat President is elected. In our robustness analysis, to account for the potential predictability of the election outcome and the swing in stock returns in anticipation of this outcome, we follow Addoum and Kumar (2016) by alternatively setting $RepubDummy_t$ equal to 1 from August prior to a Republican President being elected, and equal to 0 from August prior to a Democrat President being elected.[17]

We define *Exposed* as a dummy variable that takes the value 1 for a firm if the coefficient estimate $\widehat{\theta_i}$ is significant at the 10% level, and 0 otherwise. We further identify whether a firm is favorably exposed to the incumbent or contender party as well as whether it is favorably exposed to the winning or losing party. In particular, *Exposed_Incumbent* (*Exposed_ Contender*) is a dummy variable that takes the value 1 for a firm if, apart from being significant, $\widehat{\theta_i} > 0$ ($\widehat{\theta_i} < 0$) when a Republican President is in office or $\widehat{\theta_i} < 0$ ($\widehat{\theta_i} > 0$) when a Democrat President is in office. Similarly, *Exposed_ Winner* (*Exposed_Loser*) is a dummy variable that takes the value 1 for a firm if, apart from being significant, $\widehat{\theta_i} > 0$ ($\widehat{\theta_i} < 0$) when a Republican President has been elected or $\widehat{\theta_i} < 0$ ($\widehat{\theta_i} > 0$) when a Democrat President has been elected.

[16] This choice ensures that there is a presidential party change during the estimation period.

[17] Arguably, apart from the 1996 *Clinton vs. Dole* contest, the rest of the elections during our sample period were particularly close for their outcome to be considered a foregone conclusion long in advance.

2.2.3.3 Aligned firms

We also consider the political geography of firms' headquarters to identify their alignment with the presidential party. To this end, we use the PAI of Kim et al. (2012), updated until 2016. PAI is a state-level composite index, which measures whether the Governor, the Senators and House Representatives as well as the majorities in the state Senate and House, respectively, belong to the same party as the President. PAI ranges from 0, when none of the above belongs to the same party as the President, to 1, when all of the above belong to the same party.

PAI allows us to identify whether a firm is geographically politically aligned with the incumbent or contender party as well as with the winning or losing party of the presidential election. To this end, *Aligned_ Incumbent* (*Aligned_ Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in the top (bottom) quartile of states according to PAI before the election, and 0 otherwise. Similarly, *Aligned_ Winner* (*Aligned_ Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in the top (bottom) quartile of states according to the PAI computed right after the election, and 0 otherwise.

In addition, to examine the effect of the degree of political alignment, we use the PAI value of the firm's headquarters state per se. Specifically, to account for potential year fixed effects in PAI and to ensure comparability across election cycles, we define *PAI** as the value of PAI in excess of its median annual value across states. Finally, to examine the effect of a shift in the degree of a firm's political alignment after the election, we define ΔPAI as the difference in PAI computed right after relative to just before the election.

2.2.3.4 Connected firms

We construct a series of variables to measure the degree of firms' political connectedness with candidates at federal elections. We make use of transaction-level data involving direct contributions of corporate Political Action Committees (PACs) to federal election candidates' PACs, which are provided by the FEC.[18] We match corporation PACs with CRSP firms by name from 1991 to 2016. The matched dataset contains 893,954 transactions from firm PACs to candidate PACs. This dataset contains candidates' details, including their party affiliation, the state/district and office for which they stood, the amount contributed by each firm PAC to each candidate PAC, and the election cycle for which this contribution was made.[19] We subsequently merge this dataset with the election results provided by the MIT Election Lab and the firms' headquarters state sourced from COMPUSTAT. Hence, we can identify whether the candidate to whom the firm PAC contributed actually ran in the general election, whether she was subsequently elected or not, and whether she was a "home candidate", i.e., a candidate in the state where the firm's headquarters are located.

Following Cooper et al. (2010), we define the variable *Num. of Connections* by counting the number of general election candidates to which the firm has directly contributed money during the past 60-month window. Moreover, we define *Connected* as a dummy variable that takes the value 1 if a firm has contributed to at least one candidate during the past 60 months, and 0 otherwise. In our robustness analysis, which is presented in Section 2.5, we alternatively explore stricter definitions of political connectedness.

[18]These data comprise all "hard money" contributions, which are typically limited to $10,000 per candidate per election cycle. See Cooper et al. (2010) for a detailed description of the FEC database on campaign contributions.

[19]The descriptive statistics of the constructed dataset, which are available upon request, are qualitatively similar to the ones reported in Cooper et al. (2010) and Akey (2015) for an earlier sample period.

To further examine whether contributing exclusively to either of the two parties has a significant effect, we define the dummy variable *Connected_Democrat_only* (*Connected_Republican_only*), which takes the value 1 if the firm has contributed to Democrat (Republican) candidates only during the past 60 months. To the contrary, the dummy variable *Connected_both* takes the value 1 if the firm has contributed to both Democrat and Republican candidates during the past 60 months.

An interesting feature of the campaign contributions dataset is that most of these firms typically donate money to both Republicans and Democrats. This activity can be interpreted as a form of political hedging. To examine the effect of this behavior, we define the dummy variable *Hedged*, which takes the value 1 for a firm if the ratio of Republican-to-Democrat candidates it has contributed to during the past 60 months lies between the 25th and 75th percentile of the corresponding distribution, among firms which have made at least one direct contribution during this period, and 0 otherwise.

2.2.3.5 Frequency and correlations of political dummy variables

Panel B of Table 2.1 reports the frequency of the political dummy variables across the six election cycles in our sample period. As discussed in Section 2.3, the characterisation of these dummy variables is made at the end of June *prior* to the November election day. For the sample of firms with optionable stocks, which are included in the subsequent empirical analysis, we find that a large fraction of firms were *Sensitive* in the 36-month window prior to the 2004 and 2008 elections. Moreover, the fraction of *Exposed* firms was approximately equal to 10% prior to the 1996, 2000, 2012, and 2016 elections, whereas this fraction increased to around 20% prior to the 2004 and 2008 elections. To the contrary, by virtue of the definition of *Aligned_Incumbent*, the fraction of firms that were politically aligned with the presidential party prior to the election remained stable, around

25%, across the six election cycles. Moreover, the fraction of firms characterised as *Connected* was approximately equal to 30%, without substantial fluctuations across the six election cycles. Hence, the propensity of firms to engage in campaign contributions did not seem to fluctuate in tandem with their sensitivity to economic policy uncertainty or their exposure to the party affiliation of the President.

Panel C of Table 2.1 reports the pairwise correlation coefficients of these dummy variables. We find that the correlations are very close to 0. This finding confirms that these dummy variables capture different dimensions of firms' political characteristics and activity. Therefore, it is meaningful to examine the potential effects of each of these characteristics on firm risk, expected return, and option trading activity.

2.3 Empirical design

2.3.1 Definition of *Election*, *PostElection*, and *Benchmark* periods

The aim of our study is to estimate the effects of political uncertainty around US presidential elections on the option-based variables defined in Section 2.2, across firms with different political characteristics. To this end, we define three periods within a presidential election cycle. The *Election* period refers to an interval of calendar days just before the November presidential election day d.[20] The *PostElection* period refers to an interval of calendar days right after the election day. To identify the differential effect of the *Election* and *PostElection* periods, we

[20]The US presidential election takes place every four years on the first Tuesday after the first Monday in November.

also need to define a *Benchmark* period, during which the corresponding option-based variable should not be affected by the political uncertainty surrounding the presidential election.

In our benchmark empirical design, we make the following choices. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval $[d-15, d-1]$. For symmetry, *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval $[d+1, d+15]$. The *Benchmark* period is the union of the calendar day intervals $[d-119,\ d-60]$ and $[d+61, d+120]$. Figure 1 visualizes the timeline of the benchmark empirical design. To ensure that our regression estimates are based on a sufficient number of observations per firm within each period, we only include firms with valid observations for the corresponding option-based variable for at least 90% of the days in each period.

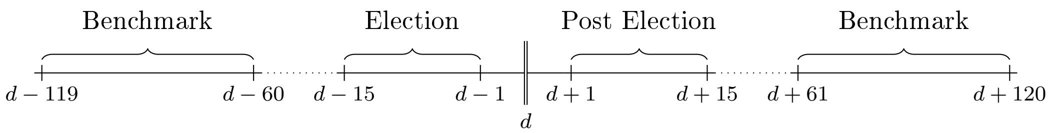

Figure 2.1: Timeline of benchmark empirical design

The definition of these three periods is motivated by the following considerations. First, we want the *Election* period to be narrowly defined just before the presidential election day. In this way, we ensure that the main event dominating this period and affecting the pricing and trading activity of options is the presidential election. In addition, using the 30-day Volatility Surface as well as individual options with expiries between 16 and 60 days ahead, we ensure that the life of the options used during this period spans the election event. Moreover, we exclude the election day itself, in case there is an early resolution of the election outcome during that day.

Second, we want the *PostElection* period to be narrowly defined just after the election day. In this way, this period primarily reflects the uncertainty surrounding the composition, orientation, and policies of the new administration, in conjuction with the potentially new majorities in the Senate and House of Representatives. Political uncertainty may persist during this period, even though the election outcome is known. The presidential winner is sworn in office on January 20, which ranges from 72 to 78 days after the election day. In the meantime, especially if a new president is elected, there is a transition period during which the new administration and its main policy priorities gradually become known.

Third, the definition of the *Benchmark* period needs to satisfy two conditions. On the one hand, it should be sufficiently close to the *Election* and the *PostElection* periods, so that the differential effects, which may be estimated in the latter two periods, are correctly attributed to the uncertainty surrounding the election event. On the other hand, it should ensure that the values of the option-based variables during this period are computed from options whose expiry does not span the election day. Given the interpolation scheme that OptionMetrics uses to compute the standardized 30-day Volatility Surface, truncating the *Benchmark* period at $d - 60$ minimizes the possibility of using information from options with expiries that span the election day.[21] Similar is the justification for the trading activity-related variables, which are computed from options with expiry between 16 and 60 calendar days ahead.

We also include the interval $[d + 61, d + 120]$ in the *Benchmark* period for two reasons. First, this choice ensures that any effect estimated during the *Election* and the *PostElection* periods is not spuriously driven by a coincidental time trend; including this post-election interval in the *Benchmark* period would neutralize the effect of such a trend. Second, this choice alleviates the potential concern that an effect identified during the *PostElection* period might be spuriously driven by a

[21] OptionMetrics uses a non-linear interpolation scheme, which for the 30-day Volatility Surface overweighs information from options with expiry around 30 days ahead. This weight becomes extremely low for options with expiry more than 45 days ahead. See the OptionMetrics manual for the exact weighting scheme.

permanent shift in the corresponding option-based variable caused by the election outcome.

Even though the above definitions of the *Benchmark*, *Election*, and *PostElection* intervals lead to the correct intepretation of the estimated differential effects, we conduct an extensive robustness analysis, which is presented in Section 2.5, to examine whether our benchmark results are sensitive to these definitions. In particular, we alternatively consider: *i*) a narrower definition of the *Election* and *PostElection* periods, *ii*) a much wider definition of the *Benchmark* period, and *iii*) a definition of the *Benchmark* period that includes only the pre-election interval.

2.3.2 Estimating the effect of sensitivity

To identify the effect of firm sensitivity to policy uncertainty on option-implied risk, expected return, option trading activity, and dispersion of investor beliefs around presidential elections, we employ a difference-in-differences framework and estimate specifications of the following regression model:

$$\begin{aligned} OptionVar_{i,t} =& \alpha + \beta_1 Election_t + \beta_2 Election_t \text{ x } Sensitive_i \\ &+ \gamma_1 PostElection_t + \gamma_2 PostElection_t \text{ x } Sensitive_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.7}$$

where $OptionVar$ denotes each of the examined option-based variables, i indexes firms, t indexes days, $Election_t$ and $PostElection_t$ are the time dummy variables defined above, and $Sensitive_i$ is the dummy variable indicating whether a firm is sensitive to economic policy uncertainty or not, as defined in Section 2.2.3.1.

To alleviate the potential concern that our estimates might be affected by reverse causality, $Sensitive_i$ is defined prior to the beginning of our sample period, i.e., prior to $d - 119$ in our benchmark timeline definition, and remains fixed throughout the election cycle. Furthermore, to mitigate the potential impact of model misspecification or omitted variables bias, we include firm-by-election cycle fixed effects. These fixed effects account for all firm characteristics, which may affect the option-based variable but are time-invariant within each election cycle, i.e., from $d - 119$ until $d + 120$ in our benchmark timeline definition. Hence, our estimation approach essentially captures the variation of the dependent variable within a firm and given an election cycle. It should also be noted that the effect during the *Benchmark* period of a firm being *Sensitive* is captured by this fixed effect.

In our full model specification, we include the daily stock return of the firm and the daily aggregate market return as control variables. In doing so, not only we control for a potential mechanistic relationship between stock returns and the corresponding option-based variable, but we also control for a potential day effect due to a market-wide shock that may affect the entire cross-section.

The coefficient β_1 (γ_1) yields the differential time effect of the *Election* (*Post-Election*) period on the option-based variable, relative to the *Benchmark* period, for a non-sensitive firm. The coefficient β_2 (γ_2) additionally captures the differential effect during the *Election* (*PostElection*) period of a firm being *Sensitive*, rather than not, ceteris paribus. More precisely, β_2 (γ_2) can be interpreted as the diff-in-diff estimate of the effect of firm sensitivity to policy uncertainty during the *Election* (*PostElection*) period. Specifically, β_2 measures the quantity ($\Delta Sensitive - \Delta NonSensitive$), where Δ indicates the difference in the option-based variable between the *Election* and the *Benchmark* periods.

Motivated by the arguments of Petersen (2009), our statistical inference throughout this study is based on two-way clustered standard errors, by firm-cycle *and* day. Though conservative in nature, using two-way clustered standard errors is deemed necessary because the innovations of our option-based variables can be highly correlated at the daily frequency and across firms; in addition, *Election* and *PostElection* are time dummy variables defined over an interval of consecutive calendar days, and hence persistent by construction. In fact, we showcase that when clustering instead standard errors by firm-cycle only, t-statistics can be substantially inflated, leading to potentially spurious inference.

2.3.3 Estimating the effect of exposure

In a similar fashion, we gauge the effect of firm exposure to the presidential party by estimating specifications of the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Exposed_i \\ &+ \gamma_1 PostElection_t + \gamma_2 PostElection_t \text{ x } Exposed_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.8}$$

where $Exposed_i$ is the dummy variable defined in Section 2.2.3.2. The rest of the variables are defined as in model (2.7). To alleviate a potential reverse causality concern, it should be stressed that $Exposed_i$ is determined prior to the beginning of the sample period in each election cycle. Moreover, its effect during the *Benchmark* period is accounted for by the firm-cycle fixed effect. Based on model (2.8), the coefficient β_2 (γ_2) can be interpreted as the diff-in-diff estimate of the effect of a firm being *Exposed*, rather than not, on the corresponding option-based variable during the *Election* (*PostElection*) period.

We further seek to estimate the effect during the *Election* period of a firm being exposed to the incumbent or contender party. Similarly, we seek to estimate the effect during the *PostElection* period of a firm being exposed to the winning or losing party. To this end, we employ the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Exposed\_Incumbent_i \\ &+ \gamma_1 PostElection_t \\ &+ \beta_3 Election_t \text{ x } Exposed\_Contender_i \\ &+ \gamma_2 PostElection_t \text{ x } Exposed\_Winner_i \\ &+ \gamma_3 PostElection_t \text{ x } Exposed\_Loser_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.9}$$

where the dummy variables $Exposed\_Incumbent_i$, $Exposed\_Contender_i$, $Exposed\_Winner_i$, and $Exposed\_Loser_i$ are also defined in Section 2.2.3.2. Here, the coefficient β_2 (β_3) can be interpreted as the diff-in-diff estimate of the effect of a firm being exposed to the incumbent (contender) party, relative to not being exposed at all, on the corresponding option-based variable during the *Election* period. Similar is the interpretation for the coefficients γ_2 and γ_3 in the *PostElection* period, for the differential effect of being exposed to the winning and losing party, respectively.[22]

2.3.4 Estimating the effect of alignment

We also estimate the effect of a firm's geographical political alignment with the incumbent or contender party during the *Election* period and the winning or losing party during the *PostElection* period by estimating specifications of the following

[22]It should be stressed again that the coefficient θ_i from model (2.6), whose sign determines whether the firm is exposed to the incumbent or contender party during the *Election* period, and whether the firm is exposed to the winning or losing party in the *PostElection* period, is estimated prior to the beginning of the *Benchmark* period. Hence, reverse causality is not an issue in this specification either.

regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Aligned\_Incumbent_i \\ &+ \beta_3 Election_t \text{ x } Aligned\_Contender_i \\ &+ \gamma_1 PostElection_t + \\ &+ \gamma_2 PostElection_t \text{ x } Aligned\_Winner_i \\ &+ \gamma_3 PostElection_t \text{ x } Aligned\_Loser_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.10}$$

where the dummy variables $Aligned\_Incumbent_i$, $Aligned\_Contender_i$, $Aligned\_Winner_i$, and $Aligned\_Loser_i$ are defined in Section 2.2.3.3. In this specification, the coefficient β_2 (β_3) can be interpreted as the diff-in-diff estimate of the effect on the corresponding option-based variable during the *Election* period of a firm's headquarters being located in a state that is politically aligned with the incumbent (contender) party, relative to not being aligned with either party. Similar is the interpretation of the coefficients γ_2 and γ_3, in the *PostElection* period, for the differential effect of a firm being aligned with the winning and losing party, respectively.

Alternatively, to estimate the effect of the strength of a firm's geographical political alignment on the corresponding option-based variable, we use the following model specification:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } PAI_i^* \\ &+ \gamma_1 PostElection_t + \gamma_2 PostElection_t \text{ x } \Delta PAI_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.11}$$

where PAI_i^* and ΔPAI_i are also defined in Section 2.2.3.3. Here, the coefficient β_2 measures the effect of the degree of a firm's political alignment with the presidential party on the option-based variable during the *Election* period, whereas the coefficient γ_2 measures the corresponding effect during the *PostElection* period due to a shift in the degree of political alignment with the presidential party right after the election.

2.3.5 Estimating the effect of connectedness

To estimate the effect of firm political connectedness via campaign contributions, we estimate specifications of the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Connected_i \\ &+ \gamma_1 PostElection_t + \gamma_2 PostElection_t \text{ x } Connected_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.12}$$

where the dummy variable *Connected*$_i$ is defined in Section 2.2.3.4. It should be stressed again that *Connected*$_i$ is defined prior to the beginning of the sample period in each election cycle, alleviating a potential reverse causality concern. Under this specification, the coefficient β_2 (γ_2) can be interpreted as the diff-in-diff estimate of the effect of a firm being *Connected*, rather than not, on the corresponding option-based variable during the *Election* (*PostElection*) period.

Alternatively, we also examine whether the strength of political connectedness has an effect on the corresponding option-based variable during the *Election* period. To this end, we consider a variation of model (2.12), where instead of the dummy variable *Connected*$_i$, we use the natural logarithm of one plus the number of candidates the firm has contributed to, i.e., *Num. of Connections.*

We further seek to examine whether the party affiliation of the candidates with whom the firm is connected yields a differential effect during the *Election* period.

To this end, we estimate the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t \\ &+ \beta_2 Election_t \text{ x } Connected\_Democrat\_only_i \\ &+ \beta_3 Election_t \text{ x } Connected\_Republican\_only_i \\ &+ \beta_4 Election_t \text{ x } Connected\_both_i \\ &+ \Phi' Controls_{i,t} \\ &+ Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.13}$$

where the dummy variables $Connected\_Democrat\_only_i$, $Connected\_Republican\_only_i$, and $Connected\_both_i$ are defined in Section 2.2.3.4. Under this specification, the coefficient β_2 (β_3) can be interpreted as the diff-in-diff estimate of the effect of a firm being connected with Democrat (Republican) candidates only, rather than not being connected at all, on the corresponding option-based variable during the *Election* period.

2.3.6 Estimating interaction effects

We further examine the potential interaction effect between firm sensitivity to policy uncertainty and political connectedness. To this end, we estimate variations of the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Sensitive_i \\ &+ \beta_3 Election_t \text{ x } Sensitive_i \text{ x } Connected_i \\ &+ \gamma_1 PostElection_t + \gamma_2 PostElection_t \text{ x } Sensitive_i \\ &+ \gamma_3 PostElection_t \text{ x } Sensitive_i \text{ x } Connected_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}. \end{aligned} \tag{2.14}$$

In this specification, the coefficient β_3 (γ_3) captures the differential effect during the *Election* (*PostElection*) period of a firm being *Connected*, rather than not, *given* that it is also *Sensitive*.

In a similar fashion, we additionally examine whether there is an interaction effect between firm sensitivity to policy uncertainty and political hedging, by replacing the dummy variable $Connected_i$ with the dummy variable $Hedged_i$ in model (2.14).

In further analysis, we also estimate the potential interaction effect between exposure to the presidential party and political connectedness, by replacing the dummy variable $Sensitive_i$ with the dummy variable $Exposed_i$ in model (2.14).

Last, we alternatively use a triple-difference framework to examine the differential effect of firm political connectedness during the *Election* period, controlling for the effect of its sensitivity status. Specifically, we estimate the following regression model:

$$\begin{aligned} OptionVar_{i,t} = \alpha &+ \beta_1 Election_t + \beta_2 Election_t \text{ x } Sensitive_i \\ &+ \beta_3 Election_t \text{ x } Connected_i \\ &+ \beta_4 Election_t \text{ x } Sensitive_i \text{ x } Connected_i \\ &+ \Phi' Controls_{i,t} + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}. \end{aligned} \tag{2.15}$$

Here, β_4 yields the triple-diff estimate of the effect of a firm being *Connected*, rather than not, *net* of the effect of being *Sensitive* or not. In particular, β_4 measures the quantity ($\Delta Connected\&Sensitive - \Delta NotConnected\&Sensitive$) $-$ ($\Delta Connected\&NonSensitive - \Delta NotConnected\&NonSensitive$), where Δ indicates the difference in the corresponding option-based variable between the *Election* and the *Benchmark* periods.

Similarly, we employ this triple-difference framework to estimate the effect of a firm being *Hedged*, rather than not, controlling for the effect of its sensitivity status, by replacing the dummy variable $Connected_i$ with the dummy variable $Hedged_i$ in model (2.15).

2.4 The effect on risk and expected return

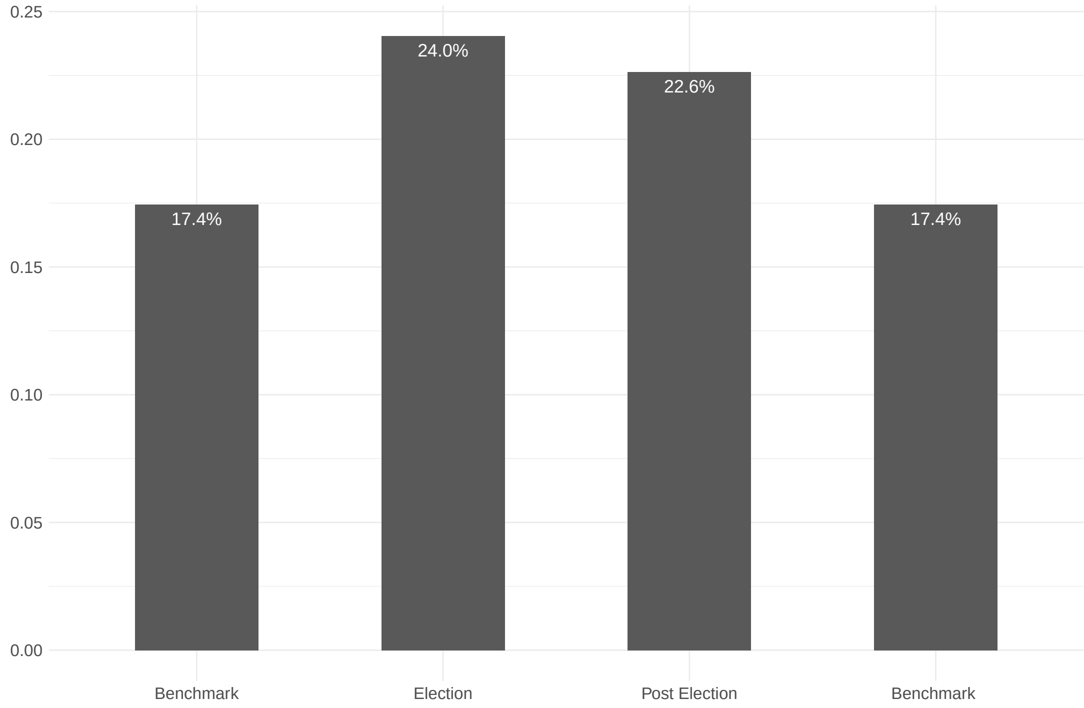

Figure 2.2: The figure shows the average level of the S&P 500 ATM during the *Benchmark*, the *Election*, and the *Post Election* periods. For a given US Presidential Election day, d, from 1996 to 2016, the Election period is defined as the interval [d-15, d-1] and the PostElection period is defined as the interval [d+1, d+15]. The benchmark period is the union of the intervals [d-119, d-60] and [d+61, d+120].

We begin the presentation of our results by examining the time series properties of volatility around the US Presidential Elections using the ATM of the S&P 500 index. Figure 2.2 shows the average level of the S&P 500 ATM during the *Benchmark*, the *Election*, and the *Post Election* periods. Table 2.2 reports the estimates of the model

$$ATM_{m,t} = \alpha + \beta_1 Election_t + \beta_2 Election_t + \phi_1 r_{mkt,t} + \epsilon_{m,t}, \tag{2.16}$$

where $ATM_{m,t}$ is the daily S&P 500 ATM and $r_{mkt,t}$ is the daily level of the market return. We find that the average ATM of the S&P 500 index during the *Benchmark* period equals 17.4% p.a. The volatility of the index increases, on average, to 24% during the *Election* period. The increase equals to 6.6% (t-stat = 5.41). Furthermore, we also find that the uncertainty persists after the election. During the *Post Election* period, the ATM of the S&P 500 index is higher by 5.2% (t-stat = 3.21) compared to the benchmark period. The estimated increases remain statistically significant when we control for the daily level of the market return.

We continue by examining the differential effect of the US Presidential Elections across all the firms of our sample. Table 2.3 reports the estimates from various specifications of model (2.7), leading to a series of interesting conclusions. First, we find that *ATM*, *LSKEW*, and *OIEXRET* exhibit a significant increase during the *Election* period across firms, regardless of their sensitivity status. This time effect remains robust, even when we control for stock-level and aggregate market returns. The statistical significance of this time effect is very strong, even though we cluster standard errors by both firm-cycle and day.[23] This effect is highly significant in economic terms too. In particular, for non-sensitive firms, we report an average increase of 5.49% in *ATM* during the *Election* period, across the six presidential election cycles in our sample. To put this figure into perspective, the average value of *ATM* during the *Benchmark* period was 46.92% p.a., indicating a percentage increase in *ATM* during the *Election* period of more than 11%. Similarly, we estimate an increase of 0.87% in *LSKEW* during the *Election* period, which corresponds to a percentage increase of more than 17% relative to the average *LSKEW* value of 4.97% p.a. during the *Benchmark* period. Moreover, we find an increase of 37 bps in *OIEXRET* during the *Election* period, which corresponds to a percentage increase of approximately 50% relative to the average *OIEXRET* value of 75 bps per month during the *Benchmark* period.

[23]Echoing the arguments of Petersen (2009), clustering standard errors only by firm-cycle in columns (1), (2), (5), and (6) of Table 2.3 yields spuriously inflated t-stats. Hence, we subsequently report t-stats based on two-way clustered standard errors.

2.4.1 The effect of sensitivity

Second, we find a significant differential effect during the *Election* period due to firm sensitivity. In particular, for *Sensitive* firms, we estimate an additional increase of 6.86% in ATM, 1.02% in *LSKEW*, and 55 bps in *OIEXRET*. As a result, the total effect of political uncertainty during the *Election* period for *Sensitive* firms amounts to an increase of more than 12% in ATM, 1.9% in *LSKEW*, and 92 bps in *OIEXRET*. These significant diff-in-diff estimates indicate that political uncertainty around presidential elections affects the risk and expected return of firms in a differential manner on the basis of their sensitivity to economic policy uncertainty. In fact, the effect of political uncertainty during the *Election* period on the price and tail risk as well as the expected return of *Sensitive* firms is twice as big as its effect on non-sensitive firms.[24]

The third interesting conclusion arising from Table 2.3 refers to the corresponding effects right after the presidential election day. We find that regardless of their sensitivity status, firms exhibit higher levels of ATM, *LSKEW*, and *OIEXRET* during the *PostElection* period, as compared to the *Benchmark* period. In fact, for non-sensitive firms, we find a relative increase of 3.84% in ATM, 0.67% in *LSKEW*, and 26 bps in *OIEXRET*. Though the magnitude of these relative increases is somewhat smaller than the corresponding increases during the *Election* period, they remain stongly significant in both economic and statistical terms.

Equally importantly, we also find a significant differential effect on the risk and expected return of *Sensitive* firms during the *PostElection* period. Specifically,

[24]For the average firm in our sample, its ATM, LSKEW, and OIXRET increase during the Election period irrespectively to whether the firm is sensitive or not. Furthermore, since the number of sensitive firms is considerably smaller to the number of non-sensitive firms, coefficient β_1 of model (2.7) may be viewed as a tight lower bound of the increase that an equally-weighted index across all the stocks of our sample would experience during the Election period. For example, the ATM for the non-sensitive firms increase by 5.49% during the Election period. Hence, we should expect that the ATM of an equally weighed index containing all the stocks of our sample to increase more than but closely to 5.49% during the Election period. In fact, in untabulated results, we estimate the specification $ATM_{i,t} = \alpha + \beta_1 Election_t + Firm \times ElectionCycleFE + \epsilon_{i,t}$ and find β_1 to be equal to 6.11% (t-stat = 5.41).

the reported diff-in-diff estimates indicate an additional increase of 6.57% in *ATM*, 0.95% in *LSKEW*, and 48 bps in *OIEXRET* for *Sensitive* firms. Hence, the total effect on *Sensitive* firms is more than twice as big as the effect on non-sensitive firms during the *PostElection* period.

In sum, we find that the political uncertainty surrounding the presidential elections leads to a highly significant increase in firms' price and tail risk. This conclusion is consistent with the findings of Kelly and Pruitt (2015) at the aggregate market level. Contributing further to this literature, we show that this increase in price and tail risk is translated into an increase in the required equity premium. Most interestingly, we document that, besides the aggregate time effect, political uncertainty exerts an additional, strong differential effect on the risk and expected return of firms that are sensitive to economic policy uncertainty. Hence, we corroborate the arguments of Brogaard and Detzel (2015) and Akey and Lewellen (2017) that sensitivity to policy uncertainty is an important firm characteristic, and we show that it acts as a fundamental source of risk during episodes of political uncertainty, such as presidential elections.

Moreover, we convincingly show that the effect of political uncertainty persists in the first few days after the presidential election, even though the election outcome itself is known. In other words, we show that the resolution of uncertainty regarding the election outcome does not immediately resolve the political uncertainty surrounding the presidential election. Its effects are still manifested in the option-implied measures of firm price and tail risk and expected return for some days after the election. These effects are significantly stronger for firms that are sensitive to policy uncertainty, stressing again the importance of this firm characteristic.

2.4.2 The effect of exposure

Next, we examine the effect of a firm's exposure to the presidential party. Table 2.4 reports the corresponding estimates from alternative specifications of models (2.8) and (2.9). It should be noted that the sample of firms used in these tests is smaller, because we require a complete history of 10-year monthly stock returns to determine whether a firm is *Exposed* or not (see Section 2.2.3.2).

Using this smaller sample of firms, we firstly confirm the previous findings regarding the time effect of political uncertainty, regardless of whether the firm is *Exposed* or not. In particular, for the non-exposed firms, we estimate an average increase of 6.18% (4.4%) in *ATM*, 0.97% (0.83%) in *LSKEW*, and 41 bps (29 bps) in *OIEXRET* during the *Election* (*PostElection*) period, relative to the *Benchmark* period.[25]

More interestingly, we report highly significant differential effects on the option-implied price risk and expected return of *Exposed* firms. In particular, we estimate an additional, strongly significant increase of 3.47% in *ATM* and 31 bps in *OIEXRET* during the *Election* period for *Exposed* firms. We also estimate an additional increase of 0.32% in *LSKEW* for *Exposed* firms, but this is significant only at the 10% level. Similarly, we find a significant differential increase in *ATM* and *OIEXRET* during the *PostElection* period for *Exposed* firms. Hence, political uncertainty renders stock options signifcantly more expensive around presidential elections, and this effect is substantially larger for *Exposed* firms, which also command a higher premium. These results lead to the conclusion that exposure to the presidential party, in the spirit of Santa-Clara and Valkanov (2003) and Addoum and Kumar (2016), is an important dimension of firm risk, which is manifested during these episodes of political uncertainty.

[25]For this smaller sample of firms, the average value during the *Benchmark* period is 42.48% p.a. for *ATM*, 5.06% p.a. for *LSKEW*, and 59 bps per month for *OIEXRET*.

Identifying the party to which firms are favorably exposed provides some further interesting insights. Specifically, estimating model (2.9), we find that the differential effects of political uncertainty are stronger for firms that are favorably exposed to the incumbent party during the *Election* period. In particular, we find a differential increase of 3.96% in *ATM*, 0.58% in *LSKEW*, and 38 bps in *OIEXRET* for *Exposed_Incumbent* firms. These differential increases are significant at the 1% level. On the other hand, the corresponding estimates for *Exposed_ Contender* firms are smaller in magnitude and insignificant for *LSKEW*. This decomposition of political exposure enables us to conclude that not only stock options of *Exposed* firms become more expensive around presidential elections, but also that the deep OTM puts of firms that are exposed to the incumbent party are substantially more expensive relative to the at-the-money options during the *Election* period. This finding reflects the willingness of investors to pay a significantly higher price to be protected against the downside tail risk of *Exposed_Incumbent* firms during this period.

We estimate interesting differential effects during the *PostElection* period too. In particular, we find a large differential increase of 7.78% in *ATM* and 59 bps in *OIEXRET* for firms that are exposed to the party that has just lost the presidential election. To the contrary, we find no significant differential effect on the risk and expected return of firms that are exposed to the winning party. In sum, our diff-in-diff estimates show that investors perceive firms that are exposed to the incumbent party as well as firms that are exposed to the loser party as substantially riskier, due to the political uncertainty surrounding the presidential election, and they require a higher premium to withhold their stock.

2.4.3 The effect of alignment

Examining the effect of geographical political alignment with the presidential party, Table 2.5 reports the estimates from various specifications of models (2.10) and (2.11).

Beyond the aggregate time effect of political uncertainty across firms, which is discussed in the previous subsections, we make a number of interesting observations regarding the differential effect of political alignment. In particular, we find that firms located in states which are politically aligned with the incumbent party experience a significant additional increase of 1.23% in *ATM*, 0.31% in *LSKEW*, and 11 bps in *OIEXRET* during the *Election* period, relative to firms that are not aligned with either party. To the contrary, firms that are aligned with the contender party do not exhibit a significant additional increase in their price and tail risk or equity premium during the same period.

An implication of this evidence is that, during the *Election* period, investors perceive the potential benefits enjoyed by firms located in states which are politically aligned with the presidential party to be at risk due to the uncertainty in the outcome of the forthcoming election. Hence, investors require a higher premium for *Aligned_Incumbent* firms, whose stock options, and especially their deep OTM puts, become substantially more expensive during this period. Interestingly, this evidence provides support for the argument of Kim et al. (2012) that geographical political alignment with the presidential party is a source of risk. In fact, we document that it can affect both the price and the tail risk of the firm during episodes of political uncertainty, such as presidential elections.

Estimating the corresponding differential effects during the *PostElection* period, we find that firms located in states which are politically aligned with the party that has just lost the presidential election exhibit an additional increase of 1.10% in *ATM* and 9 bps in *OIEXRET*, relative to firms that are not aligned with either party. We do not find any differential effect on the tail risk of these firms. Moreover, our diff-in-diff estimates show no additional increase in the risk or expected return of firms that are geographically politically aligned with the party that has just won the election.

We further examine the effect of the strength of political alignment. Columns (3) and (6) in Table 2.5 lead to the conclusion that the higher the degree of political alignment with the presidential party, the greater the increase in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* period. In particular, a firm with a PAI value equal to 0.25 in excess of the median value in the corresponding election cycle would exhibit an additional increase of 0.96% in *ATM*, 0.19% in *LSKEW*, and more than 9 bps in *OIEXRET* during the *Election* period. Moreover, we estimate that a firm experiencing a reduction in its state-level PAI value by 0.5 right after the presidential election would exhibit an additional increase of 1.34% in *ATM* and more than 11 bps in *OIEXRET* during the *PostElection* period.

Taken together, these results show that the effects of political uncertainty are typically stronger among firms that either risk losing the benefits of being politically aligned with the presidential party in the forthcoming election or have just ceased being aligned with the presidential party due to the election outcome. Even though the magnitude of these differential effects is somewhat smaller than the corresponding effects reported above due to firm sensitivity and exposure, we conclude that geographical political alignment is a particularly important firm characteristic that determines the manifestation of political uncertainty around presidential elections.

2.4.4 The effect of connectedness

We also consider the effect of political connectedness on firm risk and expected return. Table 2.6 presents the estimates from various specifications of models

(2.12) and (2.13).

We report no significant differential effect on the *ATM* and *OIEXRET* of *Connected* firms during the *Election* period. To the contrary, we find that *Connected* firms exhibit an additional increase of 0.37% in *LSKEW* during this period. Hence, investors are ready to pay a significantly higher price for the relatively deep OTM puts of *Connected* firms during the *Election* period, but this does not translate into a higher required premium for the stocks of these firms. We derive very similar conclusions when we alternatively consider stricter definitions of political connectedness in our robustness analysis (see Section 2.5.2.3).

We further examine whether using the actual number of candidates with whom a firm is connected, instead of a dummy variable, to capture the strength of political connectedness, leads to different conclusions. Column (3) of Table 2.5 reports the corresponding estimates. We still find no significant effect on *ATM*, whereas the relationship of *OIEXRET* with the number of connected politicians becomes significantly negative, though very small in magnitude. Moreover, the positive effect of political connectedness on *LSKEW* during the *Election* period remains intact.

Motivated by the arguments of Cooper et al. (2010), we additionally consider whether contributing exclusively to candidates of either party gives rise to a differential effect during the *Election* period. Estimating model (2.13), we find no evidence that contributing to Democrat or Republican candidates only has a differential effect on firm risk or expected return. In fact, the differential positive effect we previously documented with respect to *LSKEW* originates from firms that contribute to candidates of both parties. In unreported results, we have also examined whether contributing exclusively to Senate or House candidates would yield a differential effect, presumably because a Senate candidate might be a stronger political connection. Again, we find no such a differential effect.

Last, we report differential effects due to political connectedness during the *Post-Election* period. In particular, we find that *Connected* firms exhibit an additional increase of 0.99% in *ATM* and 0.28% in *LSKEW* during this period, though the latter effect is marginally significant.

In sum, our results lead to the conclusion that being politically connected is associated with an additional increase in equity tail risk around presidential elections. However, we find no evidence that politically connected firms command an additional equity premium during these episodes of political uncertainty. Hence, we remain sceptical of whether a risk-based mechanism can explain the findings of Cooper et al. (2010) on the positive correlation between the strength of firm political connectedness and future stock returns.

2.4.5 Interaction effects

Motivated by the arguments of Akey and Lewellen (2017), we further examine the potential interaction effects between firm sensitivity and political connectedness. Table 2.7 presents the estimates from alternative specifications of models (2.14) and (2.15).

First, we test whether political connectedness is an amplifying or a mitigating mechanism with respect to the strong effect of political uncertainty, which is documented in Section 2.4.1 for *Sensitive* firms. We find that political connectedness amplifies the effect on *LSKEW* for *Sensitive* firms during the *Election* and *PostElection* periods. In particular, firms that are both *Connected* and *Sensitive* exhibit an additional increase of 1.14% (1.45%) in *LSKEW* during the *Election* (*PostElection*) period, as compared to non-*Connected* but *Sensitive* firms. Political connectedness also exerts a differential effect on the *ATM* of *Sensitive* firms, but this effect is not statistically significant. We find no statistical significance for this effect, even if we cluster standard errors by firm-cycle only (see column (4) of Table 2.6). Moreover, there is no significant interaction effect with respect to *OIEXRET*.

Second, we gauge the differential effect on the risk and expected return of a firm being *Connected*, rather than not, controlling for the effect of being *Sensitive* or not. Column (3) in Table 2.7 reports the corresponding triple-diff estimates. Interestingly, we find that political connectedness significantly increases *LSKEW* by 0.88% during the *Election* period, net of the effect of firm sensitivity. We also estimate an increase of 0.72% in *ATM* that can be purely attributed to political connectedness, but this triple-diff estimate is statistically insignificant. The corresponding effect on *OIEXRET* is negligible.

In sum, we find no evidence that being *Connected* acts as a mitigating factor with respect to the effect of political uncertainty around presidential elections. To the contrary, being *Connected* aggravates the effect on the downside tail risk of *Sensitive* firms. Moreover, being *Connected* significantly increases the relative expensiveness of deep OTM puts during the *Election* period, net of the effect of the firm's sensitivity status.

In a further attempt to examine whether there is a mechanism that attenuates the effect of political uncertainty on *Sensitive* firms, we also consider the role of political hedging. To this end, we re-estimate model (2.14), after replacing the dummy variable $Connected_i$ with the dummy variable $Hedged_i$, which is defined in Section 2.2.3.4.[26] Table 2.8 reports the corresponding results. Overall, we find no significant evidence that those *Sensitive* firms which are also *Hedged* experience a reduction in their risk or expected return during the *Election* period, as compared to the *Sensitive* firms which are not *Hedged*.

[26] We have defined a firm as *Hedged* or not in terms of the ratio of Republican-to-Democrat candidates that its PAC has contributed to. For robustness, we have alternatively defined the dummy variable *Hedged* in terms of the ratio between total dollar contributions to Republican and Democrat candidates, expressed as a percentage of firm market value. Using this alternative definition of the dummy variable *Hedged*, the corresponding estimates, which are available upon request, lead to very similar conclusions.

In addition, column (3) in Table 2.8 reports the triple-diff estimate of the effect of a firm being *Hedged*, rather than not, accounting for the effect of being *Sensitive* or not. Again, we find no evidence that being politically *Hedged* leads to a reduction in firm risk or expected return during the *Election* period. Hence, we conclude that political hedging does not play a distinct role with respect to the effects of political uncertainty around presidential elections.

Last, we also examine the potential interaction effect between political connectedness and exposure to the presidential party. To this end, we re-estimate model (2.14), after replacing the dummy variable $Sensitive_i$ with the dummy variable $Exposed_i$. Table 2.A1 in the Appendix presents the corresponding results. We find that if a firm is *Exposed*, then being also *Connected* leads to a sizeable, but statistically insignificant, reduction in its *ATM*, *LSKEW*, and *OIEXRET* during the *Election* period. Hence, there is some evidence, albeit statistically insignificant, that political connectedness can partly mitigate the effect of political uncertainty for *Exposed* firms.

2.5 Robustness analysis

2.5.1 Alternative definitions of *Benchmark*, *Election*, and *PostElection* periods

Section 2.3.1 provides a detailed justification for the definition of the *Benchmark*, *Election*, and *PostElection* periods that are used in the benchmark empirical analysis. To address the potential concern that the main conclusions of our analysis might be driven by this specific definition, we perform a number of robustness tests, employing alternative definitions.

First, we use a much wider definition for the *Benchmark* period, which now contains the union of the calendar days $[d-179, d-30]$ and $[d+31, d+180]$. This wider definition ensures that the differential effects we estimate during the *Election* and *PostElection* periods are genuinely driven by the political uncertainty surrounding the presidential election. In fact, this much wider *Benchmark* period now covers almost an entire calendar year around the presidential election day, and hence it should embed the effect of any other political or economic event, apart from the election itself. Table 2.9 reports the estimates for the effect of firm sensitivity to economic policy uncertainty on risk and expected return, using this alternative definition.[27] Comparing the results reported in Table 2.9 with the corresponding results reported in Table 2.3, we conclude that both the aggregate time effects of political uncertainty and the differential effects of firm sensitivity are very robust to the use of this much wider *Benchmark* period.

Second, we alternatively use a narrower definition for the *Election* and *PostElection* periods. In particular, *Election* is now a dummy variable that takes the value of 1 for the calendar days in the interval $[d-8, d-1]$, and *PostElection* is a dummy variable that takes the value of 1 for the calendar days in the interval $[d+1, d+8]$. This narrower definition ensures that the differential effects we estimate during the *Election* and *PostElection* periods are indeed driven by the political uncertainty surrounding the presidential election, since the latter is certainly the dominant event in financial markets during this very narrow time period. Table 2.A2 in the Appendix presents the corresponding results using these narrower definitions. Comparing them with the benchmark results reported in Table 2.3, we confirm that both the overall increase in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* and *PostElection* periods and the corresponding differential increases for *Sensitive* firms are genuinely driven by the political uncertainty surrounding the presidential

[27]It should be noted that, to alleviate a potential reverse causality concern, the characterisation of firms as *Sensitive* or not is again made *prior* to the beginning of this alternative *Benchmark* period.

election. If anything, the estimated differential increase in *ATM* and *LSKEW* is even stronger using these narrower definitions.

Third, we alternatively define the *Benchmark* period to contain the interval of calendar days $[d - 119, d - 60]$ only. Including only this pre-election interval in the *Benchmark* period alleviates the potential concern that the results reported in Section 2.4 might be affected by a potential sharp reduction in firm risk and expected return in the months following the presidential election. In that case, including the interval $[d + 61, d + 120]$ in the definition of the *Benchmark* period would underestimate the level of firm risk and expected return, leading to an overestimation of the differential effects during the *Election* and *PostElection* periods. Table 2.A3 in the Appendix reports the corresponding results using this alternative definition of the *Benchmark* period. Comparing these results with the benchmark results reported in Table 2.3, we find that the estimated time effects due to political uncertainty remain intact. Moreover, we report larger diff-in-diff estimates of the effect of firm sensitivity on *ATM*, *LSKEW*, and *OIEXRET*, particularly during the *Election* period. Hence, we conclude that, if anything, the inclusion of the interval $[d+61, d+120]$ in the definition of the *Benchmark* period reduces, rather than increases, the magnitude of the differential effects that we estimate around presidential elections.

In sum, the economic and statistical significance of our benchmark results is not driven by the specific definitions of the three periods made in our main empirical design. In fact, alternative definitions yield even stronger diff-in-diff estimates of the effect of firm sensitivity on risk and expected return. We have also performed the same robustness analysis for the effects of the other corporate political characteristics that we examine in this study. The corresponding results, which are readily available upon request, confirm that our benchmark conclusions regarding the differential effects of political exposure, alignment, and connectedness on firm risk and expected return are not particularly sensitive to alternative defnitions of the *Benchmark*, *Election*, and *PostElection* periods.

2.5.2 Alternative definitions of political dummy variables

Our benchmark analysis is based on the political dummy variables defined in Section 2.2.3. Here, we perform a number of robustness checks using alternative definitions of these variables.

2.5.2.1 Sensitive firms

We examine variations of the benchmark approach we used to define a firm as *Sensitive* or not. In particular, on the basis of the regression model (2.5), we alternatively define a firm as *Sensitive* when: *i*) the coefficient estimate $\widehat{\delta_i}$ is significant at the 5% level, instead of the 10% level, *ii*) the coefficient estimate $\widehat{\delta_i}$ is significant at the 10% level, but it is now estimated using the past 24-month window, instead of the past 36-month window, or *iii*) the coefficient estimate $\widehat{\delta_i}$ is significant at the 10% level, but it is now estimated using a variation of the EPU Index of Baker et al. (2016); this alternative index is constructed using also tax code expiration and economic forecaster disagreement data, apart from the frequency of newspaper articles. We have repeated our benchmark analysis using each of these three alternative definitions of the dummy variable *Sensitive*. The corresponding results, which are available upon request, yield very similar conclusions to the ones discussed in Section 2.4.1, regarding the differential effect of firm sensitivity on *ATM*, *LSKEW*, and *OIEXRET* around presidential elections.

We also employ alternative definitions of the dummy variable *Sensitive* using different specifications of model (2.5). In particular, we include MUI as an additional regressor in (2.5) and define a firm as *Sensitive*, if the coefficient estimate $\widehat{\delta_i}$ from this augmented model is significant at the 10% level. Table 2.A4 in the Appendix presents the corresponding results using this alternative definition. These results are qualitatively similar to the ones reported in Table 2.3. *Sensitive* firms exhibit a significant differential increase in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* and *PostElection* periods, in addition to the overall time effect that is observed during these periods. Nevertheless, it should be mentioned that the magnitude of these differential effects is now lower relative to our benchmark results. Due to the non-negligible correlation between the EPU Index and MUI, this alternative approach essentially characterizes a firm as *Sensitive* with respect to the component of EPU Index that is orthogonal to macroeconomic uncertainty. Hence, this alternative definition of the dummy variable *Sensitive* does not fully account for the differential effect of sensitivity to economic policy uncertainty on firm risk and expected return.

In addition, we alternatively define the dummy variable *Sensitive* after including the S&P 500 VIX as an additional regressor in (2.5). Table 2.A5 in the Appendix reports the corresponding results using this alternative definition. The results are qualitatively similar to the ones reported in our benchmark analysis, indicating that *Sensitive* firms exhibit a differential increase in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* and *PostElection* periods. However, the magnitude of these differential effects is substantially lower relative to the benchmark results, and it is only marginally statistically significant for *LSKEW*. The explanation for this reduction in the magnitude of the differential effects lies in the strong correlation between the EPU Index and VIX (see Baker et al., 2016, for a related discussion). Hence, characterizing a firm as *Sensitive* only with respect to the component of the EPU Index that is orthogonal to market volatility fails to fully account for the differential effect of firm sensitivity to economic policy uncertainty on risk and expected return around presidential elections.

2.5.2.2 Exposed firms

Our benchmark analysis for the effect of political exposure utilized the dummy variable *Exposed*, which was defined on the basis of the regression model (2.6). In this model specification, $RepubDummy_t$ is set equal to 1 from November after a Republican President is elected, and equal to 0 from November after a Democrat President is elected. In contrast, based on the findings of Abramowitz (1988, 2008) that the presidential election outcome is predictable, Addoum and Kumar (2016) alternatively set $RepubDummy_t$ equal to 1 from August prior to a Republican President being elected, and equal to 0 from August prior to a Democrat President being elected. To alleviate the concern that our benchmark results might be affected by a potential mischaracterisation of *Exposed* firms, we repeat our analysis using this alternative definition of $RepubDummy_t$.

Table 2.A6 in the Appendix reports the corresponding results for the effect of political exposure on firm risk and expected return. The results are very similar to the ones reported in Table 2.4. Actually, the differential effect of political exposure on *LSKEW* is now strongly significant. It should be further noted that the fraction of firms characterised as *Exposed* across the electoral cycles, using this alternative definition of $RepubDummy_t$, is very similar to the one reported in Panel B of Table 2.1. Hence, we conclude that *Exposed* firms exhibit a significant differential increase in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* and *PostElection* periods, regardless of the exact definition of $RepubDummy_t$.

2.5.2.3 Connected firms

A firm is defined as *Connected* in the benchmark analysis, if it has contributed to at least one federal election candidate during the past 60 months. Arguably, contributing to a single or a few candidates only may not be sufficient for a firm to establish particularly strong political connections. Here, we alternatively explore stricter definitions of corporate political connectedness.

First, we define *Connected** as a dummy variable that takes the value 1 if the number of candidates the firm has contributed to during the past 60 months is higher than the corresponding median value across firms with positive contributions, and 0 otherwise. As a result of this stricter definition, the fraction of firms that are characterised as *Connected** in each election cycle is half of the corresponding fraction reported in Panel B of Table 2.1. Table 2.A7 in the Appendix reports the results from estimating model (2.12) using this alternative definition of political connectedness. These results confirm the conclusions we derived in our benchmark analysis. In particular, we find a significant differential increase in *LSKEW* for *Connected** firms during the *Election* and *PostElection* periods. To the contrary, there is no significant differential effect on the *ATM* or *OIEXRET* of *Connected** firms during the *Election* period.

Second, we define the dummy variable *Connected_HQState*, which takes the value 1 if a firm has contributed to a candidate who has been elected in the state of its headquarters during the past 60 months, and 0 otherwise. In addition, the variable *Num. of Connections_HQState* counts the number of the candidates to whom the firm has contributed and who have been elected in the state of its headquarters during the past 60 months. Arguably, contributing to a "home" candidate, who also gets elected, constitutes a stronger form of political connection. Table 2.A8 in Appendix presents the corresponding estimates using these two stricter measures of political connectedness. In sum, the reported results are very similar to the ones presented in Table 2.6, confirming the conclusions of our main analysis in Section 2.4.4.

2.5.3 Subsample of big- and mid-cap firms

Our benchmark analysis is based on a sample of firms with optionable stocks. We have additionally imposed a number of filters to ensure the reliability of the values of the option-based variables. As a result, our sample consists of firms which are, on average, much bigger in terms of capitalization relative to the standard cross-section of firms that is examined in most empirical asset pricing studies. Nevertheless, we perform an additional robustness test to alleviate the potential concern that our benchmark results might be primarily driven by the smaller capitalization firms in our sample, limiting the economic significance of the estimated differential effects. In particular, we repeat our analysis using only firms that are constituents of the S&P 500 and the S&P Mid-Cap 400 Indices in the corresponding electoral cycle. This sample selection naturally reduces the number of firms included in this robustness analysis, which now ranges from 493 in 1996 to 740 in 2008. Table 2.10 reports the corresponding results for the effect of firm sensitivity on risk and expected return.

Using this subsample of big- and mid-cap firms, we firstly confirm that *ATM*, *LSKEW*, and *OIEXRET* exhibit, on average, a significant increase during the *Election* and *PostElection* periods. Moreover, comparing the results in Table 2.10 with the corresponding results reported in Table 2.3, we find that the diff-in-diff estimate of the effect of firm sensitivity on *ATM*, *LSKEW*, and *OIEXRET* is even larger in this subsample of firms, particularly during the *Election* period. Hence, we conclude that the economic significance of the differential effect of sensitivity to policy uncertainty on risk and expected return is actually stronger for big- and mid-cap firms, relative to what our benchmark results indicate.[28]

[28]We have also performed the same robustness analysis for the effects of political exposure, alignment, and connectedness, using this subsample of big- and mid-cap firms. The corresponding results yield conclusions that are very similar to the ones derived in our benchmark analysis.

2.5.4 Placebo tests with "pseudo" election days

We conclude our robustness analysis by conducting placebo tests to alleviate any remaining concerns that our results might be an artefact of the empirical design or that they might be caused by "luck". To this end, we repeat our benchmark empirical analysis by alternatively using combinations of "pseudo" election dates.

In particular, we draw 10,000 combinations of six "pseudo" election dates $\tilde{d}$, one from each of the six election cycles in our sample period. This choice ensures that all six election cycles are represented in each combination of "pseudo" election dates. Each "pseudo" election day $\tilde{d}$ is drawn from the interval between the end of April, prior to the actual November election, and the end of August after the election. In the spirit of Kelly et al. (2016), the only restriction we impose is that the "pseudo" election day $\tilde{d}$ cannot occur within 30 days from the actual election day d.

For each combination of the six "pseudo" election days, we estimate specifications of model (2.7), where the *Benchmark*, *Election*, and *PostElection* periods are defined as in our benchmark empirical design, but now relative to the "pseudo" election day $\tilde{d}$. To alleviate any concern regarding reverse causality, we still characterise a firm as *Sensitive* or not prior to the beginning of the corresponding "pseudo"-*Benchmark* period.

Table 2.11 reports the results from these placebo tests. Specifically, it reports the mean estimate of each coefficient across the 10,000 combinations of the "pseudo" election days, along with the corresponding coefficient estimate from Table 2.3, which is derived using the actual presidential election days. We also report the placebo p-value, which shows the fraction of the placebo coefficient estimates that are higher than the actual estimate of the corresponding coefficient.

We find that the average placebo coefficient estimates are *negative* for all three option-implied measures of firm risk and expected return. This holds true for the estimates of the differential time effect during the *Election* and *PostElection* periods (i.e., coefficients β_1 and γ_1 in model (2.7)) as well as the diff-in-diff estimates of the effect of firm sensitivity (i.e., coefficients β_2 and γ_2 in model (2.7)). As a result, we confirm that the large positive differential effects reported in our benchmark analysis are not simply an artefact of the employed empirical design.

Moreover, we find that the placebo p-values are very low for all estimates across the three measures. Hence, these falsification tests suggest that the estimated increases in *ATM*, *LSKEW*, and *OIEXRET* during the *Election* and *PostElection* periods, and the corresponding estimated differential increases for *Sensitive* firms, using the actual presidential election days, are significantly greater than what would have been estimated with randomly selected "pseudo" election days. In other words, the magnitude of our benchmark estimates can be genuinely attributed to the politicaly uncertainty surrounding the actual presidential election days; it could not be spuriously caused by "luck" or combinations of other, non-election events.

2.5.5 Scheduled Earnings Announcements during the *Election* period

A prominent example of firm-specific scheduled events that affect the firm's ATM is the earnings announcement drift. Dubinsky et al. (2018) find that a firm's implied volatility increases before an earnings announcement, the term structure of its implied volatility is negatively sloped, and the implied volatility discontinuously falls after the announcement. Motivated by their study, we first assess whether there is an earnings season surrounding the presidential election that could affect our result. Secondly, we test the effect of the presidential elections on the term structure of the ATM of the market and of individual stocks.

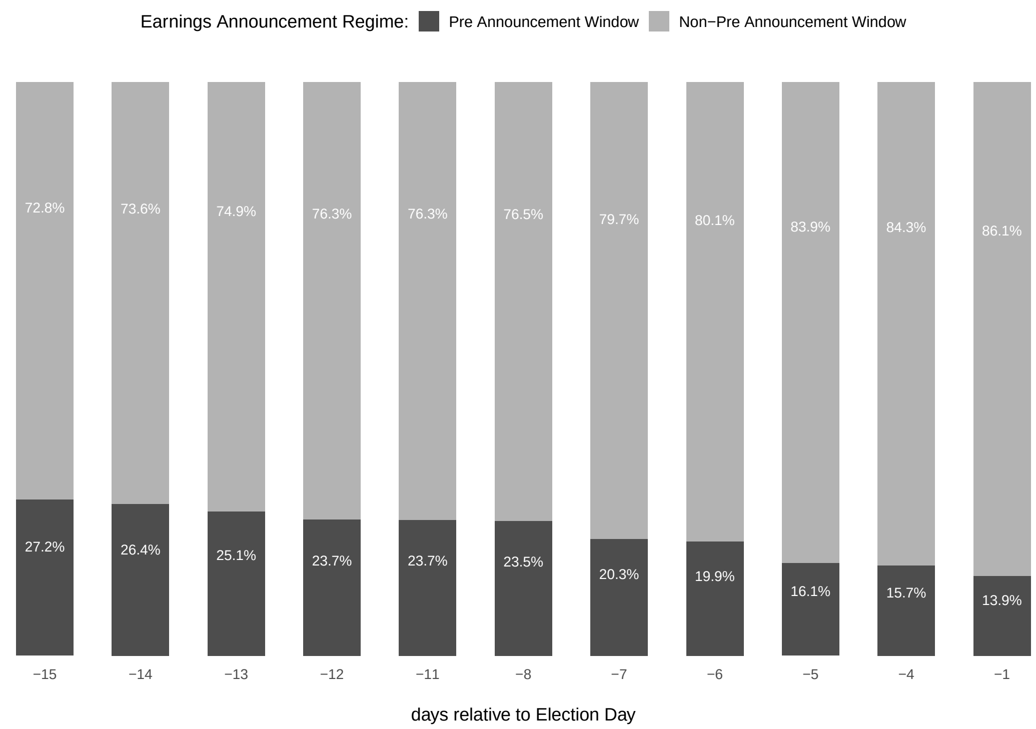

Figure 2.3: For each US Presidential Election day, d, the Figure shows the fraction of stocks in each Earnings Announcement Regime for the days during the Election period, ranging from $d - 15$ to $d - 1$. We consider a stock to be in the Pre Announcement Window regime if it has a scheduled announcement in the following 7 days. If the next earnings announcement is after 7 days, we consider the stock to be in the Non-Pre Announcement Window regime.

To gauge the possible effect that earnings announcements have on our results we work as follows. First, for each firm in our sample, we source the dates of its scheduled earnings announcements from Compustat. Second, on each day, we split the stocks for which we have earning announcement data into two categories. In the first category, which we call *Pre Announcement Window* regime, we assign all the stocks that have a scheduled earnings announcement in one of the following seven days. In the second category, which we call the *Non-Pre Announcement Window regime*, we assign the rest of the stocks. Figure 2.3 shows the fraction of stocks in each category for each day of the Election period.

The percentage of firms in the *Pre Announcement Window* regime ranges from 14% to 27% across the days of the *Election* period. Furthermore, we find that across all the days of the *Election* period, more than 78% of our firm-day observations are in a *Non-Pre Announcement Window* regime. The percentage increases to 82% in our narrower definition for the *Election* period, where *Election* is a dummy variable that takes the value of 1 for the calendar days in the interval $[d-8, d-1]$. Hence, our sample is dominated by firm-day observations, where firms are in the *Non-Pre Announcement Window*. This finding alleviates the potential concern that our results could be systematically affected by an earnings season surrounding the presidential elections.

Furthermore, we test the effect of the presidential elections on the slope of the ATM term structure. We proxy for the slope of the term structure with the difference between the ATM measure using the implied volatilities for options with maturity equal to 60 days (ATM^{2m}) minus the ATM,

$$ATM^{Sl} = ATM^{2m} - ATM.$$

We test the effect that the Election and the Post Election periods have on the term-structure of the S&P 500 and the average stock by the regression models

$$\begin{aligned} ATM^{Sl}_{m,t} =& \alpha + \beta_1 Election_t + \gamma_1 PostElection_t + \\ & + \phi_2 r_{mkt,t} + \epsilon_{m,t} \end{aligned} \tag{2.17}$$

and

$$\begin{aligned} ATM^{Sl}_{i,t} =& \alpha + \beta_1 Election_t + \gamma_1 PostElection_t + \\ & + \phi_1 r_{i,t} + \phi_2 r_{mkt,t} + \\ & + Firm \text{ x } Election\ Cycle\ FE + \epsilon_{i,t}, \end{aligned} \tag{2.18}$$

respectively. Table 2.12 reports the results. The slope of the S&P 500 ATM term structure is on average positive and equals 0.49% during the *Benchmark* period. In contrast, the term structure of the index becomes negatively sloped during both the Election and the Post Election periods, as it decreases by -1.86% (t-stat $= -5.04$) and -1.07% (t-stat $= -2.63$), respectively. Similarly, for the average stock, we find that the slope of the term-structure decreases by -1.5% (t-stat $= -5.14$) and -0.4% (t-stat $= -2.92$) during the Election and the Post Election periods, respectively. Hence, there are two main differences between the presidential elections and firm-specific earnings announcements. First, the presidential elections affect both the market overall and the average stock individually. Second, in contrast to the earnings announcements, the uncertainty created by the presidential elections is not resolved abruptly after the event but persists during the *PostElection* period as well.

2.6 The effect on option trading activity and the dispersion of investor beliefs

In this Section, we examine the effect of political uncertainty around presidential elections on various dimensions of option trading activity and the dispersion of investor beliefs. Apart from testing the existence of an aggregate time effect during the *Election* or *PostElection* period, we also examine whether there are differential effects during these periods for firms that are *Sensitive*, *Exposed*, *Aligned*, or *Connected*.

2.6.1 Option trading activity

Table 2.13 presents the estimates for the effect of political uncertainty on $TOTVOL$. Interestingly, we find significant differential time effects. In particular, relative to the *Benchmark* period, $TOTVOL$ significantly increases during the *Election* period, whereas it significantly decreases during the *PostElection* period. The magnitude of these time effects is quite large. Given the normalised definition of the option trading variables (see Section 2.2.2.2), the reported estimates indicate that the average increase in $TOTVOL$ during the *Election* period is approximately equal to 30% of the average $TOTVOL$ value from January to June prior to the election.[29] Similarly, relative to the *Benchmark* period, we find a significant reduction in $TOTVOL$ during the *PostElection* period, which is approximately equal to 20% of its average value in the prior period from January to June.[30]

Next, we examine whether there is a differential effect on $TOTVOL$ for firms with specific political characteristics. Even though there is some evidence that firms which are sensitive to policy uncertainty and firms that are geographically politically aligned with the presidential party exhibit a differential increase in $TOTVOL$ during the *Election* period, this evidence is not statistically significant. The only diff-in-diff estimate that is significant at the 5% level indicates a substantial increase in $TOTVOL$ during the *PostElection* period for firms exposed to the party that has just lost the presidential election.

As an alternative measure of trading activity in the option market, we also utilize $TOTOI$. Table 2.A9 in the Appendix reports the corresponding estimates. Similar to $TOTVOL$, we find a highly significant increase in $TOTOI$ during the *Election* period. To the contrary, the estimated decrease in $TOTOI$ during the *PostElection* period is statistically insignificant. Examining the differential effects due to firm political characteristics, the most interesting finding is that firms which are aligned

[29] Alternatively, since the average $TOTVOL$ value during the *Benchmark* period is 1.26, the coefficient estimate of 0.293 for the *Election* period, which is reported in Panel A of Table 2.13, indicates a percentage increase of approximately 23% relative to the *Benchmark* period.

[30] Since $TOTVOL$ is computed from options with expiry between 16 and 60 days ahead, this trading activity cannot be driven by potentially abnormal trading patterns of near-expiry options. Another potential concern is that our results might be reflecting a periodical option trading pattern due to the definition of the *Election* and *PostElection* periods and the expiry cycle of the options. To address this potential concern, we alternatively use a much narrower definition of these two periods. Similar to the robustness check discussed in Section 2.5.1, *Election* takes the value 1 for the calendar days in the interval $[d-8, d-1]$, and *PostElection* takes the value 1 for the calendar days in the interval $[d+1, d+8]$, where d is the presidential election day. We also construct $TOTVOL$ using options that expire between 8 and 60 days ahead. The corresponding results, which are available upon request, yield a very similar pattern; we estimate again a significant average increase in $TOTVOL$ during the narrower *Election* period and a significant average decrease in $TOTVOL$ during the narrower *PostElection* period. Hence, our estimates reflect a genuine time effect due to the political uncertainty surrounding the presidential election, and they are not spuriously driven by the option expiry cycle.

with the presidential party exhibit a significant additional increase in *TOTOI* during the *Election* period.

To gauge whether these trading activity patterns are more pronounced in the option rather than the underlying stock market, we also estimate the corresponding effects on the *TOTVOL-to-STOCKVOL* ratio. Results are reported in Table 2.A10 in the Appendix. Interestingly, we find a significant increase in *TOTVOL-to-STOCKVOL* during the *Election* period, and a significant decrease in *TOTVOL-to-STOCKVOL* during the *PostElection* period. Hence, we conclude that the documented effects on option trading activity around presidential elections do not simply mimic similar effects on stock trading activity; the effects on option trading activity are much more pronounced. In addition, we find that firms which are aligned with the presidential party exhibit an additional increase in *TOTVOL-to-STOCKVOL* during the *Election* period.

Overall, we find strong evidence that option trading activity is substantially increased during the *Election* period. This increase could be a reflection of an increased dispersion of investor beliefs due to political uncertainty, or it could be driven by hedging or speculative motives in anticipation of stock price shifts due to the election outcome. In fact, open interest and the option-to-stock volume ratio have been proposed as proxies for investor hedging demand (see *inter alia* Roll, Schwartz, and Subrahmanyam, 2010; Hong and Kostovetsky, 2012; Johnson and So, 2012). In an attempt to understand better the underlying mechanism that leads to the documented patterns, we further examine components of the option trading activity across different option moneyness levels.

To this end, we firstly consider the trading activity in OTM puts, which is commonly regarded to reflect hedging demand by pessimistic investors (see *inter alia* Dennis and Mayhew, 2002; Beber and Brandt, 2006; Stilger et al., 2017). Table 2.14 reports the estimates for the effect of political uncertainty on *OTMPUTVOL*.

We find significant differential time effects, which are similar to the ones reported for *TOTVOL*. In particular, relative to the *Benchmark* period, we find a significant increase (decrease) in *OTMPUTVOL* during the *Election* (*PostElection*) period. However, we do not report significant differential effects on *OTMPUTVOL* due to corporate political characteristics, with the exception of an additional increase during the *PostElection* period for firms which are exposed to the party that has just lost the presidential election as well as for *Connected* firms.

To examine whether these time effects on the trading activity of OTM puts simply reflect the corresponding time effects on total option trading volume reported in Table 2.13, we utilize the ratio *OTMPUTVOL-to-TOTVOL*. Table A11 in the Appendix reports these estimates. Using this standardised measure of trading activity in OTM puts, we find that the average increase during the *Election* period remains large and significant, whereas the effect during the *PostElection* period disappears. Moreover, we find no evidence of a significant differential effect for *Sensitive*, *Exposed*, *Aligned*, or *Connected* firms during the *Election* period. We only estimate a significant additional increase for *Connected* firms during the *PostElection* period.

Last, we consider the effect of political uncertainty on the trading of activity of OTM calls, which may reflect speculative demand by optimistic investors (see, for example, Bali and Murray, 2013; Filippou, Garcia-Ares, and Zapatero, 2017; Gkionis, Kostakis, Skiadopoulos, and Stilger, 2018) or simply volatility trading. Table 2.15 presents the corresponding results using *OTMCALLVOL*. We document a very strong increase in *OTMCALLVOL* during the *Election* period, and a significant decrease during the *PostElection* period. Interestingly, we also find a significant additional increase in the *OTMCALLVOL* of *Sensitive* firms during the *Election* period, and a significant additional decrease during the *PostElection* period for firms which are exposed to the party that has just won the presidential election.

In sum, the previous analysis leads to a number of interesting conclusions. First, we document that there is a significant increase in option trading activity during the *Electio*n period and a corresponding decrease during the *PostElection* period. Second, these shifts in option trading activity are much more pronounced than the corresponding shifts in stock trading activity. Hence, the importance of the option market as trading venue increases in the run up to presidential elections. Third, we find similar patterns in the trading activity of both OTM puts and OTM calls. As a result, the documented shifts in total trading activity cannot be exclusively attributed to hedging or speculative motives. Fourth, we find no consistent evidence that firm political characteristics exert a significant differential effect on total option trading activity or its components. Therefore, the significant differential increase in ATM or $LSKEW$ around presidential elections for *Sensitive*, *Exposed*, *Aligned*, and *Connected* firms, which is documented in Section 2.4, cannot be attributed to a trading pressure mechanism along the lines of Bollen and Whaley (2004) and Garleanu et al. (2009).

2.6.2 Dispersion of investor beliefs

Motivated by the previous conclusions, we further examine whether political uncertainty affects the dispersion of investor beliefs. To this end, we utilize *DISPOI*, which is defined in Section 2.2.2.2. The results reported in Table 2.16 indicate a number of significant effects. Specifically, we find a large increase in the dispersion of investor beliefs during the *Election* and *PostElection* periods, as compared to the *Benchmark* period. Given an average *DISPOI* value of 1.14 during the *Benchmark* period, the differential estimate of 0.173 (0.164) for the *Election* (*PostElection*) period, which is reported in Panel A of Table 2.16, corresponds to a relative percentage increase of more than 15% (14%).

Even more interestingly, we find that corporate political characteristics exert a significant differential effect too. In particular, *Sensitive* firms experience a very large additional increase in *DISPOI* during both the *Election* and the *PostElection* period. A substantial additional increase in *DISPOI* is reported for *Exposed* firms too. Identifying the party to which firms are exposed, we find that these positive diff-in-diff estimates are strongly significant for firms which are exposed to the incumbent party, and for firms which are exposed to the party that has just lost the election. We also estimate a significant additional increase in *DISPOI* for firms that are aligned with the incumbent presidential party during the *Election* period. Last, we find only marginally significant evidence of a small differential reduction in *DISPOI* for firms that are *Connected* during the *Election* period.

Concluding, our results convincingly show that not only political uncertainty is priced in the option market, but it also substantially increases the dispersion of investor beliefs with respect to future price shifts. Contributing to the literature, we show that firm political characteristics constitute an additional factor that can render these beliefs even more disperse during episodes of political uncertainty. In particular, we highlight that, during the *Election* period, investors form significantly more disperse beliefs regarding the value of the firms that are sensitive to economic policy uncertainty as well as the firms that are exposed to or are geographically politically aligned with the presidential party. Overall, this evidence explains to an extent the corresponding differential effects reported in Section 2.4 for *ATM, LSKEW,* and *OIEXRET*, and it is consistent with the argument that volatility and the equity premium are associated with heterogeneity in investor beliefs.

2.7 Conclusions

This study contributes to the growing literature that examines the effects of political uncertainty on financial markets by providing comprehensive evidence on the manifestations of this type of uncertainty around US presidential elections. Using information from the option market, we examine the time and cross-sectional differential effects of these episodes of political uncertainty on the expected return of equity, price and tail risk, as well as on option trading activity and the dispersion of investor beliefs.

We find that political uncertainty surrounding presidential elections is priced in the option market, leading to a highly significant increase in the equity price and tail risk and the equity premium. Most interestingly, we document that, besides the aggregate time effect, political uncertainty exerts strong differential effects on the basis of corporate political characteristics. This is particularly true for firms that are sensitive to economic policy uncertainty and firms that are exposed to or are geographically politically aligned with the presidential party. Moreover, we convincingly show that the effect of political uncertainty persists in the first few days after the presidential election, even though the election outcome itself is known.

Our results corroborate the arguments of Kim et al. (2012), Brogaard and Detzel (2015), and Akey and Lewellen (2017) that geographical political alignment with the presidential party and sensitivity to policy uncertainty, respectively, are important firm characteristics, which act as fundamental sources of risk during episodes of political uncertainty. Similar is the conclusion for firms whose stock returns are favorably or adversely exposed to the party affiliation of the President. To the contrary, we only find limited evidence that direct political connectedness, in the form of campaign contributions, is a source of tail risk. These findings call for further research to understand the causes and implications of these corporate political features and activities.

In an attempt to understand the trading mechanisms that give rise to these effects, we also examine the patterns in option trading activity and the dispersion of investor beliefs around presidential elections. Whereas we find a significant overall increase in option trading activity in the run up to the election, indicating an increase in the importance of the option market as trading venue, we find no consistent evidence that corporate political characteristics exert significant differential effects on this trading activity. Therefore, the documented differential effects on firm risk and expected return cannot be attributed to a trading pressure mechanism.

On the other hand, we estimate a significant differential effect on the dispersion of investor beliefs for sensitive, exposed, and aligned firms. Hence, we demonstrate another channel through which political uncertainty affects financial markets. It causes an increase in the heterogeneity of investor beliefs, which, in turn, is associated with an increase in option-implied risk and the equity premium. Future research could shed more light on the types of active traders and their motives during episodes of political uncertainty.

Table 2.1: Summary Statistics

Panel A shows the summary statistics for the daily option-based variables. The sample period in the benchmark results corresponds to the union of the calendar day intervals: [*d*-119, *d*-60], [*d*-15, *d*-1], [*d*+1, *d*+15], and [*d*+61, *d*+120], where *d* is the US Presidential Election day from 1996 to 2016. *ATM* denotes the firm-level, annualized 30-day volatility implied by at-the-money options. *LSKEW* measures the difference between the annualized 30-day volatility implied by out-of-the-money put options and *ATM*. *OIEXRET* stands for the 30-day option-implied expected excess return of Martin and Wagner (2018), expressed in basis points (bps) per month. *TOTVOL* denotes the daily total trading volume of option contracts. *TOTOI* shows the daily total open interest for option contracts. *TOTVOL-to-STOCKVOL* denotes the daily ratio of *TOTVOL* divided by the stock trading volume. *OTMPUTVOL* stands for the daily total trading volume of out-of-the-money put options. *OTMPUTVOL-to-TOTVOL* shows the daily ratio of *OTMPUTVOL* divided by *TOTVOL* plus 0.01 to avoid zero values in the denominator. *OTMCALLVOL* corresponds to the daily total trading volume of out-of-the-money call options. *DISPOI* measures the daily dispersion of options' open interest across levels of moneyness. Trading volume and open interest are computed from options with expiry between 16 and 60 days ahead. *TOTVOL*, *TOTOI*, *TOTVOL-to-STOCKVOL*, *OTMPUTVOL*, *OTMPUTVOL-to-TOTVOL*, *OTMCALLVOL*, and *DISPOI* are normalized to be expressed as multiples of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. Panel B shows the frequency of the political dummy variables per election cycle. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Aligned_Incumbent* is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top quartile states according to the election year's Political Alignment Index (PAI) of Kim et al. (2012). *Connected* is a dummy variable that takes the value 1 for a firm if its Political Action Committee (PAC) has contributed money to the PAC of a US House, Senate, or Presidential candidate during the past 60 months. *Sensitive*, *Exposed*, *Aligned_Incumbent*, and *Connected* are defined at the end of June prior to the November Presidential Election day *d*. Panel C shows the correlation matrix of the political dummy variables.

Panel A: Option-Based Variables

Variable	Mean	St. Dev.	5^{th} pctl	25^{th} pctl	Median	75^{th} pctl	95^{th} pctl	Obs.
ATM (%, p.a.)	50.61	26.90	19.13	30.19	44.12	64.94	102.84	936,959
LSKEW (%, p.a.)	5.23	7.01	-2.21	1.68	3.82	7.20	17.36	936,959
OIEXRET (bps, per month)	95.0	129.7	-6.1	14.2	49.5	128.7	350.6	895,231
TOTVOL	1.29	3.34	0.00	0.04	0.32	1.08	5.39	886,019
TOTOI	1.34	1.91	0.04	0.26	0.81	1.66	4.34	886,019
TOTVOL-to-STOCKVOL	1.17	2.56	0.00	0.06	0.39	1.15	4.81	886,017
OTMPUTVOL	1.48	5.97	0.00	0.00	0.00	0.49	6.18	875,782
OTMPUTVOL-to-TOTVOL	1.11	2.96	0.00	0.00	0.00	0.85	5.67	875,782
OTMCALLVOL	1.32	4.65	0.00	0.00	0.03	0.70	5.79	883,123
DISPOI	1.20	0.87	0.33	0.69	1.00	1.42	2.80	514,044

Panel B: Frequency of Political Dummy Variables per Election Cycle

	Sample for Sensitivity		Sample for Political Exposure		Sample for Political Alignment		Sample for Connectedness	
Election Cycle	**No. of Firms**	**Fraction *Sensitive***	**No. of Firms**	**Fraction *Exposed***	**No. of Firms**	**Fraction *Aligned_ Incumbent***	**No. of Firms**	**Fraction *Connected***
1996	900	5.56%	536	12.31%	1,057	25.7%	900	29.4%
2000	1,180	5.76%	694	10.81%	1,434	24.1%	1,180	27.5%
2004	1,385	12.06%	892	19.17%	1,447	25.7%	1,385	27.9%
2008	1,399	23.02%	1,053	24.41%	1,527	25.5%	1,399	31.0%
2012	1,398	5.51%	1,063	7.43%	1,507	24.7%	1,398	32.3%
2016	1,487	6.79%	1,150	10.35%	1,703	22.5%	1,487	29.9%

Table 2.1: (Continued)

Panel C: Correlation of Political Dummies

	Sensitive	***Exposed***	***Aligned_ Incumbent***	***Connected***
Sensitive	1			
Exposed	0.058	1		
Aligned_Incumbent	-0.001	0.011	1	
Connected	0.007	-0.020	0.014	1

Table 2.2: The Effect of the US Presidential Elections on the Market

This Table shows the coefficient estimates for the regression model (2.16). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [d-15, d-1], where d is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [d+1, d+15]. The benchmark period is the union of the intervals [d-119, d-60] and [d+61, d+120]. ATM denotes the annualized 30-day volatility implied by at-the-money options of the S&P 500 index. $r_{mkt,t}$ denotes the S&P 500 return. Standard errors are clustered at the election year (*cycle*) level. t-statistics are reported in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	S&P 500 ATM (%, p.a.)	
	(1)	*(2)*
Election	*6.60****	*6.80****
	(3.16)	*(3.21)*
PostElection	*5.19***	*4.65***
	(2.57)	*(2.48)*
S&P 500 return		*-1.88***
		(-2.18)
Constant	*17.45****	*17.44****
	(47.93)	*(49.23)*
Clusters	*Cycle*	*Cycle*
Observations	*636*	*636*
R-squared adj.	*0.048*	*0.098*

Table 2.3: The Effect of Sensitivity

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM* denotes the firm-level, annualized 30-day volatility implied by at-the-money options. *LSKEW* measures the difference between the annualized 30-day volatility implied by out-of-the-money put options and *ATM*. *OIEXRET* stands for the 30-day option-implied expected excess return of Martin and Wagner (2018), expressed in basis points (bps) per month. Control variables include the daily stock and market returns. Standard errors are clustered either at the firm-by-cycle level (one-way) or at the firm-by-cycle & day levels (two-way). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: ATM (%, p.a.)							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Election	*5.42****	*5.47****	*5.42****	*5.47****	*5.41****	*5.49****	*5.41****	*5.49****
	(37.33)	*(37.45)*	*(5.41)*	*(5.45)*	*(37.36)*	*(37.50)*	*(5.90)*	*(5.89)*
Election x Sensitive	*6.74****	*6.82****	*6.74****	*6.82****	*6.73****	*6.86****	*6.73****	*6.86****
	(12.01)	*(12.06)*	*(5.73)*	*(5.80)*	*(12.01)*	*(12.11)*	*(6.07)*	*(6.13)*
PostElection					*4.03****	*3.84****	*4.03****	*3.84****
					(27.96)	*(27.66)*	*(4.42)*	*(4.45)*
PostElection x Sensitive					*6.88****	*6.57****	*6.88****	*6.57****
					(11.78)	*(11.71)*	*(5.80)*	*(5.77)*
Controls	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Fixed Effects	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*
Clusters	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*
Observations	*732,409*	*732,409*	*732,409*	*732,409*	*817,579*	*817,579*	*817,579*	*817,579*
R-squared adj.	*0.840*	*0.841*	*0.840*	*0.841*	*0.839*	*0.841*	*0.839*	*0.841*

Table 2.3: (Continued)

	Panel B: LSKEW (%, p.a.)							
Election	*0.91****	*0.87****	*0.91****	*0.87****	*0.90****	*0.87****	*0.90****	*0.87****
	(17.31)	*(16.74)*	*(4.28)*	*(4.71)*	*(17.22)*	*(16.65)*	*(4.37)*	*(4.87)*
Election x Sensitive	*1.08****	*1.02****	*1.08****	*1.02****	*1.08****	*1.02****	*1.08****	*1.02****
	(6.07)	*(5.81)*	*(3.50)*	*(4.08)*	*(6.09)*	*(5.82)*	*(3.54)*	*(4.15)*
PostElection					*0.59****	*0.67****	*0.59****	*0.67****
					(11.61)	*(13.18)*	*(3.44)*	*(4.23)*
PostElection x Sensitive					*0.80****	*0.95****	*0.80****	*0.95****
					(4.59)	*(5.39)*	*(3.05)*	*(4.09)*
Controls	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Fixed Effects	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*
Clusters	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*
Observations	*732,409*	*732,409*	*732,409*	*732,409*	*817,579*	*815,579*	*817,579*	*817,579*
R-squared adj.	*0.295*	*0.302*	*0.295*	*0.302*	*0.295*	*0.303*	*0.295*	*0.303*
	Panel C: OIEXRET (bps, per month)							
Election	*36.4****	*36.9****	*36.4****	*36.9****	*36.3****	*37.0****	*36.3****	*37.0****
	(32.86)	*(32.98)*	*(4.20)*	*(4.24)*	*(32.89)*	*(33.04)*	*(4.51)*	*(4.55)*
Election x Sensitive	*54.2****	*54.9****	*54.2****	*54.9****	*54.1****	*55.2****	*54.1****	*55.2****
	(12.19)	*(12.25)*	*(5.25)*	*(5.36)*	*(12.19)*	*(12.28)*	*(5.49)*	*(5.64)*
PostElection					*28.1****	*26.4****	*28.1****	*26.4****
					(27.26)	*(26.86)*	*(4.13)*	*(4.18)*
PostElection x Sensitive					*50.7****	*48.1****	*50.7****	*48.1****
					(11.75)	*(11.69)*	*(5.64)*	*(5.69)*
Controls	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Fixed Effects	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle*
Clusters	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*	*Firm-Cycle*	*Firm-Cycle*	*Firm-Cycle & Day*	*Firm-Cycle & Day*
Observations	*699,165*	*699,165*	*699,165*	*699,165*	*780,399*	*780,399*	*780,399*	*780,399*
R-squared adj.	*0.716*	*0.719*	*0.716*	*0.719*	*0.715*	*0.721*	*0.715*	*0.721*

Table 2.4: The Effect of Political Exposure

This Table shows the coefficient estimates for alternative specifications of the regression models (2.8) and (2.9). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: ***ATM (%, p.a.)***					
	(1)	(2)	(3)	(4)	(5)	(6)
Election	6.12***	6.17***	6.17***	6.10***	6.18***	6.18***
	(5.59)	(5.62)	(5.62)	(6.10)	(6.05)	(6.05)
Election x Exposed	3.38***	3.44***		3.37***	3.47***	
	(3.95)	(4.03)		(4.17)	(4.24)	
Election x Exposed_Incumbent			3.90***			3.96***
			(3.23)			(3.37)
Election x Exposed_Contender			2.83***			2.81***
			(3.22)			(3.40)
PostElection				4.60***	4.40***	4.40***
				(4.63)	(4.68)	(4.68)
PostElection x Exposed				3.90***	3.73***	
				(4.28)	(4.31)	
PostElection x Exposed_Winner						0.85
						(1.26)
PostElection x Exposed_Loser						7.78***
						(5.93)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	509,008	568,231	568,231	568,231
R-squared adj.	0.827	0.829	0.829	0.828	0.831	0.831

	Panel B: ***LSKEW (%, p.a.)***					
Election	1.01***	0.97***	0.97***	1.00***	0.97***	0.97***
	(4.13)	(4.55)	(4.55)	(4.23)	(4.74)	(4.74)
Election x Exposed	0.36	0.32*		0.36	0.32*	
	(1.61)	(1.67)		(1.63)	(1.70)	
Election x Exposed_Incumbent			0.58**			0.58***
			(2.53)			(2.58)
Election x Exposed_Contender			-0.03			-0.03
			(-0.10)			(-0.10)
PostElection				0.75***	0.83***	0.83***
				(3.88)	(4.62)	(4.62)
PostElection x Exposed				0.18	0.26	
				(0.90)	(1.40)	
PostElection x Exposed_Winner						0.22
						(1.01)
PostElection x Exposed_Loser						0.30
						(1.09)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	509,008	568,231	568,231	568,231
R-squared adj.	0.305	0.312	0.312	0.305	0.312	0.312

Table 2.4: (Continued)

	Panel C: *OIEXRET (bps, per month)*					
Election	40.7***	41.2***	41.2***	40.6***	41.3***	41.3***
	(4.33)	(4.37)	(4.37)	(4.64)	(4.67)	(4.67)
Election x Exposed	30.1***	30.7***		30.1***	30.9***	
	(4.01)	(4.10)		(4.19)	(4.31)	
Election x			37.8***			37.9***
Exposed_Incumbent			(3.61)			(3.71)
Election x			21.1***			21.5***
Exposed_Contender			(2.91)			(3.16)
PostElection				31.1***	29.2***	29.2***
				(4.27)	(4.33)	(4.33)
PostElection x Exposed				30.0***	28.6***	
				(4.35)	(4.44)	
PostElection x						7.2
Exposed_Winner						(1.59)
PostElection x						59.2***
Exposed_Loser						(5.70)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	486,413	486,413	486,413	542,956	542,956	542,956
R-squared adj.	0.697	0.701	0.701	0.699	0.707	0.708

Table 2.5: The Effect of Political Alignment

This Table shows the coefficient estimates for alternative specifications of the regression models (2.10) and (2.11). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *PAI** is the state-level value of the Political Alignment Index (PAI) of Kim et al. (2012) in excess of its median value across states in the same year. Δ*PAI* is the change in the state-level PAI right after the election. *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Election	5.86***	5.71***	6.10***	5.89***	5.76***	6.12***
	(5.46)	(5.39)	(5.56)	(5.93)	(5.86)	(6.01)
Election x Aligned_Incumbent	1.15***	1.30***		1.09***	1.23***	
	(2.97)	(3.18)		(3.00)	(3.17)	
Election x Aligned_Contender		0.45			0.41	
		(1.38)			(1.33)	
*Election x PAI**			3.83***			3.84***
			(3.56)			(3.76)
PostElection				4.27***	4.26***	4.49***
				(4.50)	(4.49)	(4.69)
PostElection x Aligned_Winner				-0.13	-0.10	
				(-0.39)	(-0.31)	
PostElection x Aligned_Loser				1.08***	1.10***	
				(3.02)	(3.05)	
PostElection x ΔPAI						-2.68***
						(-4.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	819,867	819,867	819,867	915,217	915,217	915,217
R-squared adj.	0.850	0.850	0.850	0.851	0.851	0.851

	Panel B: *LSKEW (%, p.a.)*					
Election	0.89***	0.82***	0.94***	0.88***	0.82***	0.93***
	(4.64)	(4.29)	(4.85)	(4.80)	(4.43)	(5.02)
Election x Aligned_Incumbent	0.25**	0.32**		0.25**	0.31**	
	(2.07)	(2.44)		(2.15)	(2.49)	
Election x Aligned_Contender		0.20			0.19	
		(1.61)			(1.58)	
*Election x PAI**			0.77***			0.75***
			(3.10)			(3.15)
PostElection				0.83***	0.83***	0.75***
				(5.00)	(4.97)	(4.54)
PostElection x Aligned_Winner				-0.19*	-0.18*	
				(-1.77)	(-1.66)	
PostElection x Aligned_Loser				-0.14	-0.13	
				(-1.09)	(-1.01)	
PostElection x ΔPAI						-0.24
						(-1.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	819,867	819,867	819,867	915,217	915,217	915,217
R-squared adj.	0.302	0.302	0.302	0.303	0.303	0.303

Table 2.5: Continued

	Panel C: *OIEXRET (bps, per month)*					
Election	40.0***	39.1***	42.2***	40.3***	39.4***	42.3***
	(4.27)	(4.24)	(4.40)	(4.61)	(4.57)	(4.73)
Election x Aligned_Incumbent	10.9***	11.8***		10.2***	11.1***	
	(3.31)	(3.40)		(3.29)	(3.37)	
Election x Aligned_Contender		2.7			2.6	
		(1.06)			(1.09)	
*Election x PAI**			37.9***			37.7***
			(4.06)			(4.25)
PostElection				29.6***	29.5***	31.6***
				(4.27)	(4.26)	(4.47)
PostElection x Aligned_Winner				-0.7	-0.6	
				(-0.33)	(-0.26)	
PostElection x Aligned_Loser				9.2***	9.3***	
				(3.28)	(3.30)	
PostElection x ΔPAI						-22.9***
						(-4.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	783,328	783,328	783,328	874,352	874,352	874,352
R-squared adj.	0.738	0.738	0.739	0.739	0.739	0.740

Table 2.6: The Effect of Connectedness

This Table shows the coefficient estimates for alternative specifications of the regression models (2.12) and (2.13). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Connected* is a dummy variable defined at the end of June prior to the November Presidential Election. It takes the value 1 for a firm if its PAC has contributed money to the PAC of a US House, Senate, or Presidential candidate in the past 60 months. *Num. of Connections* denotes the number of candidates that the firm PAC has contributed to. *Connected_Democrat_only* (*Republican_only*) is a dummy variable that takes the value 1 for a firm if its PAC has contributed money only to Democrat (Republican) candidates during the past 60 months years. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*				
	(1)	(2)	(3)	(4)	(5)
Election	6.00***	6.05***	6.14***	6.05***	6.07***
	(5.39)	(5.43)	(5.42)	(5.43)	(5.86)
Election x Connected	0.40	0.40			0.39
	(1.11)	(1.11)			(1.10)
Election x ln(1+Num. of Connections)			0.03		
			(0.38)		
Election x Connected_Democrat_only				0.70	
				(0.23)	
Election x Connected_Republican_only				0.39	
				(0.25)	
Election x Connected_both				0.39	
				(1.09)	
PostElection					4.21***
					(4.40)
PostElection x Connected					0.99***
					(2.85)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	732,409	732,409	815,579
R-squared adj.	0.839	0.840	0.840	0.840	0.840
	Panel B: *LSKEW (%, p.a.)*				
Election	0.91***	0.87***	0.87***	0.87***	0.86***
	(3.97)	(4.57)	(4.53)	(4.57)	(4.66)
Election x Connected	0.37**	0.37**			0.37***
	(2.53)	(2.54)			(2.65)
Election x ln(1+Num. of Connections)			0.99**		
			(2.49)		
Election x Connected_Democrat_only				-0.68	
				(-0.73)	
Election x Connected_Republican_only				-0.01	
				(-0.03)	
Election x Connected_both				0.39***	
				(2.65)	
PostElection					0.68***
					(4.10)
PostElection x Connected					0.28*
					(1.74)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	732,409	732,409	815,579
R-squared adj.	0.294	0.302	0.302	0.302	0.303

Table 2.6: (Continued)

	Panel C: *OIEXRET (bps, per month)*				
Election	42.7***	43.2***	44.1***	43.2***	43.4***
	(4.29)	(4.34)	(4.35)	(4.34)	(4.66)
Election x Connected	-2.1	-2.1			-2.1
	(-0.85)	(-0.84)			(-0.85)
Election x ln(1+Num. of Connections)			-1.2**		
			(-2.19)		
Election x Connected_Democrat_only				14.5	
				(0.46)	
Election x Connected_Republican_only				-2.6	
				(-0.23)	
Election x Connected_both				-2.2	
				(-0.88)	
PostElection					31.3***
					(4.34)
PostElection x Connected					0.3
					(0.11)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	699,165	699,165	699,165	699,165	780,399
R-squared adj.	0.714	0.717	0.717	0.717	0.718

Table 2.7: The Interaction Effect between Sensitivity and Connectedness

This Table shows the coefficient estimates for alternative specifications of the regression models (2.14) and (2.15). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are clustered either at the firm-by-cycle level (one-way) or at the firm-by-cycle & day levels (two-way). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: *ATM (%, p.a.)*

	(1)	(2)	(3)	(4)	(5)
Election	5.42***	5.47***	5.39***	5.49***	5.49***
	(5.41)	(5.45)	(5.45)	(37.50)	(5.89)
Election x Sensitive	6.43***	6.51***	6.59***	6.55***	6.55***
	(5.67)	(5.74)	(5.69)	(9.81)	(5.98)
Election x Connected			0.27		
			(0.78)		
Election x Sensitive x Connected	0.98	0.99	0.72	0.99	0.99
	(0.80)	(0.80)	(0.57)	(0.83)	(0.81)
PostElection				3.84***	3.84***
				(27.66)	(4.45)
PostElection x Sensitive				6.08***	6.08***
				(9.18)	(5.48)
PostElection x Sensitive x Connected				1.56	1.56
				(1.32)	(1.27)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	732,409	732,409	732,409	817,579	817,579
R-squared adj.	0.840	0.841	0.841	0.841	0.841

Panel B: *LSKEW (%, p.a.)*

	(1)	(2)	(3)	(4)	(5)
Election	0.91***	0.87***	0.79***	0.87***	0.87***
	(4.28)	(4.71)	(4.45)	(16.65)	(4.87)
Election x Sensitive	0.72**	0.66**	0.74***	0.67***	0.67**
	(2.24)	(2.53)	(2.75)	(3.27)	(2.54)
Election x Connected			0.27*		
			(1.88)		
Election x Sensitive x Connected	1.16***	1.15***	0.88**	1.14***	1.14***
	(2.96)	(2.97)	(2.28)	(3.10)	(3.01)
PostElection				0.67***	0.67***
				(13.18)	(4.23)
PostElection x Sensitive				0.50**	0.50**
				(2.50)	(2.02)
PostElection x Sensitive x Connected				1.45***	1.45***
				(3.83)	(3.34)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	732,409	732,409	732,409	817,579	817,579
R-squared adj.	0.295	0.302	0.302	0.303	0.303

Table 2.7: (Continued)

	Panel C: ***OIEXRET (bps, per month)***				
Election	36.4***	36.9***	37.7***	37.0***	37.0***
	(4.20)	(4.24)	(4.30)	(33.04)	(4.55)
Election x Sensitive	54.4***	55.1***	54.3***	55.4***	55.4***
	(5.19)	(5.29)	(5.20)	(10.20)	(5.53)
Election x Connected			-2.6		
			(-1.08)		
Election x Sensitive x Connected	-0.6	-0.6	2.1	-0.5	-0.5
	(-0.07)	(-0.06)	(0.22)	(-0.06)	(-0.06)
PostElection				26.4***	26.4***
				(26.86)	(4.18)
PostElection x Sensitive				46.9***	46.9***
				(9.51)	(5.48)
PostElection x Sensitive x Connected				3.7	3.7
				(0.43)	(0.44)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	699,165	699,165	699,165	780,399	780,399
R-squared adj.	0.716	0.719	0.719	0.721	0.721

Table 2.8: The Interaction Effect between Sensitivity and Hedging

This Table shows the coefficient estimates for alternative specifications of the regression models (2.14) and (2.15), using *Hedged* instead of *Connected* firms. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *Hedged* is a dummy variable defined at the end of June prior to the November Presidential Election. It takes the value 1 for a firm if its PAC has contributed money to the PAC of a US House, Senate, or Presidential candidate during the past 60 months and the ratio of Republican-to-Democrat candidates it has contributed to lies between the 25th and 75th percentiles of the corresponding cross-sectional distribution. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are clustered either at the firm-by-cycle level (one-way) or at the firm-by-cycle & day levels (two-way). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: ***ATM (%, p.a.)***				
	(1)	(2)	(3)	(4)	(5)
Election	5.42***	5.47***	5.45***	5.49***	5.49***
	(5.41)	(5.45)	(5.42)	(37.50)	(5.89)
Election x Sensitive	6.76***	6.84***	6.85***	6.88***	6.88***
	(5.70)	(5.77)	(5.78)	(11.17)	(6.08)
Election x Hedged			0.13		
			(0.32)		
Election x Sensitive x Hedged	-0.11	-0.10	-0.23	-0.11	-0.11
	(-0.07)	(-0.07)	(-0.16)	(-0.07)	(-0.07)
PostElection				3.84***	3.84***
				(27.66)	(4.45)
PostElection x Sensitive				6.56***	6.56***
				(10.63)	(5.69)
PostElection x Sensitive x Hedged				0.01	0.01
				(0.01)	(0.01)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	732,409	732,409	732,409	817,579	817,579
R-squared adj.	0.840	0.841	0.841	0.841	0.841
	Panel B: ***LSKEW (%, p.a.)***				
Election	0.91***	0.87***	0.83***	0.87***	0.87***
	(4.28)	(4.71)	(4.53)	(16.65)	(4.87)
Election x Sensitive	1.01***	0.95***	1.00***	0.95***	0.95***
	(3.20)	(3.67)	(3.80)	(4.95)	(3.71)
Election x Hedged			0.31*		
			(1.89)		
Election x Sensitive x Hedged	0.46	0.46	0.15	0.46	0.46
	(1.00)	(1.01)	(0.34)	(1.05)	(1.01)
PostElection				0.67***	0.67***
				(13.18)	(4.23)
PostElection x Sensitive				0.83***	0.83***
				(4.27)	(3.46)
PostElection x Sensitive x Hedged				0.78*	0.78*
				(1.85)	(1.71)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	732,409	732,409	732,409	817,579	817,579
R-squared adj.	0.295	0.302	0.302	0.303	0.303

Table 2.8: (Continued)

	Panel C: *OIEXRET (bps, per month)*				
Election	36.4***	36.9***	37.7***	37.0***	37.0***
	(4.20)	(4.24)	(4.26)	(33.04)	(4.55)
Election x Sensitive	55.5***	56.3***	55.5***	56.6***	56.6***
	(5.25)	(5.35)	(5.32)	(11.38)	(5.63)
Election x Hedged			-5.1*		
			(-1.73)		
Election x Sensitive x Hedged	-8.3	-8.3	-3.2	-8.3	-8.3
	(-0.79)	(-0.78)	(-0.29)	(-0.77)	(-0.78)
PostElection				26.4***	26.4***
				(26.86)	(4.18)
PostElection x Sensitive				49.5***	49.5***
				(10.78)	(5.65)
PostElection x Sensitive x Hedged				-8.8	-8.8
				(-0.93)	(-0.95)
Controls	No	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle	Firm-Cycle&Day
Observations	699,165	699,165	699,165	780,399	780,399
R-squared adj.	0.716	0.719	0.719	0.721	0.721

Table 2.9: The Effect of Sensitivity, Wider Benchmark Period

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7), using a wider benchmark period. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-179, *d*-30] and [*d*+31, *d*+180]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*			
	(1)	(2)	(3)	(4)
Election	5.65***	5.66***	5.65***	5.67***
	(5.02)	(5.03)	(5.24)	(5.25)
Election x Sensitive	5.60***	5.61***	5.59***	5.63***
	(5.16)	(5.17)	(5.30)	(5.32)
PostElection			4.26***	4.17***
			(3.99)	(4.05)
PostElection x Sensitive			5.60***	5.44***
			(4.96)	(4.99)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	1,522,389	1,522,389	1,632,418	1,632,418
R-squared adj.	0.814	0.814	0.814	0.815
	Panel B: *LSKEW (%, p.a.)*			
Election	0.92***	0.89***	0.91***	0.89***
	(4.08)	(4.46)	(4.13)	(4.55)
Election x Sensitive	0.72**	0.69***	0.72**	0.69***
	(2.54)	(2.99)	(2.56)	(3.01)
PostElection			0.62***	0.71***
			(3.52)	(4.29)
PostElection x Sensitive			0.55**	0.72***
			(2.22)	(3.22)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	1,552,389	1,552,389	1,632,418	1,632,418
R-squared adj.	0.257	0.265	0.260	0.268
	Panel C: *OIEXRET (bps, per month)*			
Election	37.1***	37.2***	37.0***	37.2***
	(3.84)	(3.86)	(3.98)	(4.01)
Election x Sensitive	47.5***	47.6***	47.5***	47.8***
	(5.03)	(5.06)	(5.13)	(5.20)
PostElection			28.6***	27.6***
			(3.61)	(3.67)
PostElection x Sensitive			43.9***	42.4***
			(5.19)	(5.27)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	1,482,204	1,482,204	1,558,596	1,558,596
R-squared adj.	0.693	0.693	0.690	0.692

Table 2.10: The Effect of Sensitivity, Sample of S&P 500 and S&P 400 Firms

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7), using firms that are constituents of the S&P 500 and the S&P MidCap 400 Indices. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*			
	(1)	(2)	(3)	(4)
Election	5.20***	5.44***	5.19***	5.56***
	(3.41)	(3.54)	(3.56)	(3.74)
Election x Sensitive	8.96***	9.24***	8.95***	9.39***
	(4.43)	(4.54)	(4.57)	(4.71)
PostElection			4.11***	3.84***
			(3.82)	(3.87)
PostElection x Sensitive			7.02***	6.56***
			(4.35)	(4.41)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	350,175	350,175	373,584	373,584
R-squared adj.	0.821	0.822	0.823	0.823
	Panel B: *LSKEW (%, p.a.)*			
Election	0.89**	0.74**	0.88**	0.76**
	(2.44)	(2.43)	(2.49)	(2.54)
Election x Sensitive	2.17***	2.00***	2.18***	2.03***
	(4.07)	(4.76)	(4.12)	(4.74)
PostElection			0.43**	0.52**
			(2.08)	(2.36)
PostElection x Sensitive			1.23***	1.39***
			(3.57)	(3.92)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	350,175	350,175	373,584	373,584
R-squared adj.	0.347	0.352	0.347	0.352
	Panel C: *OIEXRET (bps, per month)*			
Election	33.5***	35.4***	33.5***	36.2***
	(2.85)	(2.95)	(2.95)	(3.11)
Election x Sensitive	67.5***	69.6***	67.4***	70.5***
	(4.15)	(4.24)	(4.25)	(4.40)
PostElection			21.0***	19.0***
			(3.03)	(3.01)
PostElection x Sensitive			47.4***	44.1***
			(4.46)	(4.57)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	341,037	341,037	363,841	363,841
R-squared adj.	0.667	0.670	0.674	0.680

Table 2.11: The Effect of Sensitivity, Placebo Estimates from Pseudo-Election Dates

This Table shows the results from the placebo tests described in Section 6.4. Alternative specifications of the regression model (2.7) are estimated using 10,000 draws of six pseudo-election days $\tilde{d}$, one for each of the six US Presidential Election cycles from 1996 to 2016. The pseudo-election day $\tilde{d}$ cannot be drawn within 30 calendar days from the actual US Presidential Election day d. For each variable, the Table reports the average placebo coefficient estimate across the 10,000 sets of pseudo-election days (Mean Placebo Est.), the corresponding coefficient estimate using the actual election days (Actual Est.), and the fraction of placebo estimates that exceed the actual estimate of the corresponding coefficient (p-value). For the placebo tests, *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [$\tilde{d}$-15, $\tilde{d}$-1]. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [$\tilde{d}$+1, $\tilde{d}$+15]. The benchmark period is the union of the intervals [$\tilde{d}$-119, $\tilde{d}$-60] and [$\tilde{d}$+61, $\tilde{d}$+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns.

		Panel A: ***ATM (%, p.a.)***			
		(1)	(2)	(3)	(4)
Election	Mean Placebo Est.	-0.79	-0.79	-0.79	-0.79
	Actual Est.	5.42	5.47	5.41	5.49
	p-value	0.002	0.002	0.002	0.002
Election x Sensitive	Mean Placebo Est.	-0.53	-0.51	-0.53	-0.51
	Actual Est.	6.74	6.82	6.73	6.86
	p-value	0.006	0.006	0.006	0.006
PostElection	Mean Placebo Est.			-1.06	-1.06
	Actual Est.			4.03	3.84
	p-value			0.005	0.006
PostElection x Sensitive	Mean Placebo Est.			-0.93	-0.92
	Actual Est.			6.88	6.57
	p-value			<0.001	<0.001
Controls		No	Yes	No	Yes
Fixed Effects		Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
		Panel B: ***LSKEW (%, p.a.)***			
Election	Mean Placebo Est.	-0.09	-0.09	-0.09	-0.09
	Actual Est.	0.91	0.87	0.90	0.87
	p-value	0.007	0.006	0.008	0.006
Election x Sensitive	Mean Placebo Est.	-0.07	-0.08	-0.07	-0.08
	Actual Est.	1.08	1.02	1.08	1.02
	p-value	0.016	0.014	0.016	0.014
PostElection	Mean Placebo Est.			-0.11	-0.11
	Actual Est.			0.59	0.67
	p-value			0.006	0.003
PostElection x Sensitive	Mean Placebo Est.			-0.13	-0.14
	Actual Est.			0.80	0.95
	p-value			0.003	<0.001
Controls		No	Yes	No	Yes
Fixed Effects		Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle

Table 2.11: (Continued)

		Panel C: *OIEXRET (bps, per month)*			
Election	Mean Placebo Est.	-4.7	-4.7	-4.7	-4.7
	Actual Est.	36.4	36.9	36.3	37.0
	p-value	0.002	0.002	0.002	0.002
Election x Sensitive	Mean Placebo Est.	-6.4	-6.2	-6.4	-6.3
	Actual Est.	54.2	54.9	54.1	55.2
	p-value	0.001	0.001	0.001	0.001
PostElection	Mean Placebo Est.			-5.4	-5.4
	Actual Est.			28.1	26.4
	p-value			<0.001	<0.001
PostElection x Sensitive	Mean Placebo Est.			-8.9	-8.8
	Actual Est.			50.7	48.1
	p-value			<0.001	<0.001
Controls		No	Yes	No	Yes
Fixed Effects		Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle

Table 2.12: The Effect on the slope of the ATM term structure

This Table shows the coefficient estimates for the regression models (2.17) and (2.18). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. ATM_i^{Sl} denotes the difference of the annualized 60-day volatility minus the annualized 30-day volatility implied by at-the-money options. ATM_m^{Sl} denotes the ATM_i^{Sl} measure for the S&P 500 index. Standard errors are clustered at the election year (*cycle*) level. *t*-statistics are reported in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	ATM_m^{Sl} *(%, p.a.)*		ATM_i^{Sl} *(%, p.a.)*	
	(1)	*(2)*	*(3)*	*(4)*
Election	*-1.86****	*-1.89****	*-1.44****	*-1.43****
	(-5.04)	*(-5.10)*	*(-5.82)*	*(-5.88)*
PostElection	*-1.07***	*-1.00***	*-0.33***	*-0.31***
	(-2.63)	*(2.52)*	*(-2.63)*	*(2.52)*
Constant	*0.49****	*0.49****		
	(13.91)	*(14.32)*		
Controls	*No*	*Yes*	*No*	*Yes*
Fixed Effects	*No*	*No*	*Firm-Cycle*	*Firm-Cycle*
Clusters	*Cycle*	*Cycle*	*Firm-Cycle&Day*	*Firm-Cycle&Day*
Observations	*636*	*636*	*817,477*	*817,477*
R-squared adj.	*0.18*	*0.22*	*0.196*	*0.197*

Table 2.13: The Effect on Total Option Trading Volume

This Table shows the coefficient estimates from regression models where the dependent variable is the daily total trading volume (*TOTVOL*) of options with expiry between 16 and 60 days ahead. *TOTVOL* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (8) and (9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression model (10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				**Panel C: Connectedness**		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.295***	0.294***	0.293***	*Election*	0.295***	0.295***	0.294***
	(4.83)	(4.81)	(4.82)		(4.72)	(4.70)	(4.70)
Election x Sensitive	0.098	0.098	0.098	*Election x Connected*	0.031	0.031	0.031
	(1.32)	(1.32)	(1.32)		(0.70)	(0.69)	(0.70)
PostElection			-0.180***	*PostElection*			-0.194***
			(-3.20)				(-3.38)
PostElection x Sensitive			-0.083	*PostElection x Connected*			0.018
			(-1.38)				(0.43)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	708,394	708,394	790,767	Observations	708,394	708,394	790,767
R-squared adj.	0.115	0.115	0.115	R-squared adj.	0.115	0.115	0.115

Table 2.13: Continued

	Panel B: Exposure				Panel D: Alignment		
Election	0.310***	0.309***	0.309***	*Election*	0.282***	0.274***	0.272***
	(4.51)	(4.52)	(4.52)		(4.62)	(4.21)	(4.20)
Election x Exposed	-0.038	-0.037		*Election x*	0.053	0.060	0.068
	(-0.59)	(-0.58)		*Aligned_Incumbent*	(1.17)	(1.28)	(1.48)
Election x Exposed_Incumbent			0.057	*Election x*		0.021	0.021
			(0.62)	*Aligned_Contender*		(0.46)	(0.46)
Election x Exposed_Contender			-0.158*	*PostElection*			-0.197***
			(-1.86)				(-3.27)
PostElection		-0.207***	-0.207***	*PostElection x*			0.033
		(-3.45)	(-3.45)	*Aligned_Winner*			(0.75)
PostElection x Exposed		0.079		*PostElection x*			-0.014
		(1.41)		*Aligned_Loser*			(-0.33)
PostElection x Exposed_Winner			0.019				
			(0.25)				
PostElection x Exposed_Loser			0.161**				
			(1.99)				
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	498,238	556,201	556,201	Observations	775,653	775,653	865,852
R-squared adj.	0.113	0.113	0.113	R-squared adj.	0.116	0.116	0.117

Table 2.14: The Effect on Trading Volume of Out-of-The-Money Put Options

This Table shows the coefficient estimates from regression models where the dependent variable is the daily total trading volume of out-of-the-money put options (*OTMPUTVOL*) with expiry between 16 and 60 days ahead. *OTMPUTVOL* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (8) and (9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression models (10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				Panel C: Connectedness		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.394***	0.390***	0.390***	*Election*	0.383***	0.379***	0.379***
	(5.18)	(5.17)	(5.14)		(4.94)	(4.93)	(4.91)
Election x Sensitive	0.105	0.101	0.102	*Election x Connected*	0.070	0.070	0.070
	(0.78)	(0.75)	(0.76)		(0.93)	(0.92)	(0.91)
PostElection			-0.196***	*PostElection*			-0.243***
			(-2.80)				(-3.48)
PostElection x Sensitive			-0.069	*PostElection x Connected*			0.129*
			(-0.57)				(1.89)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	699,885	699,885	781,259	Observations	699,885	699,885	781,259
R-squared adj.	0.085	0.086	0.086	R-squared adj.	0.085	0.086	0.086

Table 2.14: (Continued)

Panel B: Exposure				Panel D: Alignment			
Election	0.417***	0.416***	0.416***	*Election*	0.396***	0.364***	0.361***
	(5.16)	(5.14)	(5.14)		(5.19)	(4.23)	(4.19)
Election x Exposed	-0.132	-0.132		*Election x Aligned_Incumbent*	-0.073	-0.040	-0.029
	(-1.20)	(-1.20)			(-1.00)	(-0.53)	(-0.38)
Election x Exposed_Incumbent			-0.111	*Election x Aligned_Contender*		0.096	0.093
			(-0.76)			(1.10)	(1.09)
Election x Exposed_Contender			-0.159	*PostElection*			-0.223***
			(-1.17)				(-2.89)
PostElection		-0.190**	-0.190**	*PostElection x Aligned_Winner*			0.053
		(-2.47)	(-2.47)				(0.77)
PostElection x Exposed		0.041		*PostElection x Aligned_Loser*			-0.009
		(0.44)					(-0.14)
PostElection x Exposed_Winner			-0.142				
			(-1.25)				
PostElection x Exposed_Loser			0.291**				
			(2.07)				
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	491,974	549,201	549,201	Observations	766,674	766,674	855,819
R-squared adj.	0.084	0.084	0.084	R-squared adj.	0.086	0.086	0.085

Table 2.15: The Effect on Trading Volume of Out-of-The-Money Call Options

This Table shows the coefficient estimates from regression models where the dependent variable is the daily total trading volume of out-of-the-money call options (*OTMCALLVOL*) with expiry between 16 and 60 days ahead. *OTMCALLVOL* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (8) and (9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression models (10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				**Panel C: Connectedness**		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.419***	0.424***	0.424***	*Election*	0.430***	0.436***	0.436***
	(6.28)	(6.39)	(6.40)		(6.22)	(6.32)	(6.33)
Election x Sensitive	0.284***	0.291***	0.290***	*Election x Connected*	0.058	0.058	0.059
	(2.73)	(2.79)	(2.78)		(0.88)	(0.88)	(0.89)
PostElection			-0.170***	*PostElection*			-0.180***
			(-2.91)				(-3.11)
PostElection x Sensitive			-0.088	*PostElection x Connected*			0.004
			(-1.14)				(0.08)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	705,988	705,988	788,076	Observations	705,988	705,988	788,076
R-squared adj.	0.091	0.092	0.091	R-squared adj.	0.091	0.092	0.091

Table 2.15: (Continued)

Panel B: Exposure			
Election	0.457***	0.457***	0.457***
	(6.20)	(6.20)	(6.20)
Election x Exposed	0.004	0.005	
	(0.05)	(0.05)	
Election x Exposed_Incumbent			0.145
			(1.11)
Election x Exposed_Contender			-0.177
			(-1.59)
PostElection		-0.155**	-0.155**
		(-2.45)	(-2.45)
PostElection x Exposed		-0.099	
		(-1.34)	
PostElection x Exposed_Winner			-0.175**
			(-2.02)
PostElection x Exposed_Loser			0.006
			(0.05)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	496,192	553,913	553,913
R-squared adj.	0.092	0.090	0.090

Panel D: Alignment			
Election	0.441***	0.445***	0.445***
	(6.58)	(6.08)	(6.09)
Election x Aligned_Incumbent	0.016	0.012	0.018
	(0.27)	(0.19)	(0.28)
Election x Aligned_Contender		-0.012	-0.017
		(-0.19)	(-0.27)
PostElection			-0.176***
			(-2.80)
PostElection x Aligned_Winner			-0.016
			(-0.31)
PostElection x Aligned_Loser			-0.003
			(-0.05)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	773,064	773,064	862,956
R-squared adj.	0.095	0.095	0.094

Table 2.16: The Effect on Dispersion of Options' Open Interest across Moneyness Levels

This Table shows the coefficient estimates from regression models where the dependent variable is the daily dispersion of open interest (*DISPOI*) across levels of moneyness for options with expiry between 16 and 60 days ahead. *DISPOI* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (8) and (9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression model (10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				**Panel C: Connectedness**		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.169***	0.172***	0.173***	*Election*	0.211***	0.214***	0.215***
	(4.32)	(4.36)	(4.65)		(4.66)	(4.71)	(5.01)
Election x Sensitive	0.273***	0.277***	0.279***	*Election x Connected*	-0.035*	-0.035*	-0.035*
	(5.13)	(5.26)	(5.31)		(-1.71)	(-1.71)	(-1.71)
PostElection			0.164***	*PostElection*			0.187***
			(3.16)				(3.42)
PostElection x Sensitive			0.329***	*PostElection x Connected*			0.033
			(4.46)				(1.33)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	412,407	412,407	460,603	Observations	412,407	412,407	460,603
R-squared adj.	0.383	0.385	0.406	R-squared adj.	0.382	0.384	0.404

Table 2.16: (Continued)

	Panel B: Exposure				Panel D: Alignment		
Election	0.194***	0.195***	0.195***	*Election*	0.185***	0.187***	0.188***
	(4.45)	(4.72)	(4.72)		(4.64)	(4.53)	(4.84)
Election x Exposed	0.106**	0.107***		*Election x*	0.090***	0.089***	0.087***
	(2.52)	(2.58)		*Aligned_Incumbent*	(2.80)	(2.72)	(2.78)
Election x Exposed_Incumbent			0.193***	*Election x*		-0.004	-0.001
			(2.95)	*Aligned_Contender*		(-0.19)	(-0.03)
Election x Exposed_Contender			-0.006	*PostElection*			0.192***
			(-0.17)				(3.43)
PostElection		0.196***	0.196***	*PostElection x*			-0.008
		(3.40)	(3.40)	*Aligned_Winner*			(-0.35)
PostElection x Exposed		0.135**		*PostElection x*			0.038
		(2.53)		*Aligned_Loser*			(1.47)
PostElection x Exposed_Winner			0.022				
			(0.53)				
PostElection x Exposed_Loser			0.281***				
			(3.18)				
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	297,757	332,545	332,545	Observations	449,945	449,945	502,532
R-squared adj.	0.391	0.410	0.411	R-squared adj.	0.395	0.395	0.416

Table 2.A1: The Interaction Effect between Political Exposure and Connectedness

This Table shows the coefficient estimates for alternative specifications of the regression model (2.14), using *Exposed* instead of *Sensitive* firms. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day, from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

		Panel A: ***ATM (%, p.a.)***	
	(1)	(2)	(3)
Election	6.12***	6.17***	6.18***
	(5.59)	(5.62)	(6.05)
Election x Exposed	3.71***	3.78***	3.81***
	(3.92)	(3.98)	(4.15)
Election x Exposed x Connected	-0.96	-0.97	-0.98
	(-0.95)	(-0.95)	(-0.96)
PostElection			4.40***
			(4.68)
PostElection x Exposed			3.96***
			(4.05)
PostElection x Exposed x Connected			-0.68
			(0.67)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	568,231
R-squared adj.	0.827	0.829	0.831
		Panel B: ***LSKEW (%, p.a.)***	
Election	1.01***	0.97***	0.97***
	(4.13)	(4.55)	(4.74)
Election x Exposed	0.41	0.37	0.0037
	(1.55)	(1.63)	(1.64)
Election x Exposed x Connected	-0.15	-0.14	-0.14
	(-0.44)	(-0.41)	(-0.42)
PostElection			0.83***
			(4.62)
PostElection x Exposed			0.08
			(0.40)
PostElection x Exposed x Connected			0.50
			(1.42)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	568,231
R-squared adj.	0.305	0.312	0.312

Table 2.A1: (Continued)

	Panel C: *OIEXRET (bps, per month)*		
Election	40.7***	41.2***	41.3***
	(4.33)	(4.37)	(4.67)
Election x Exposed	34.3***	35.0***	35.2***
	(4.02)	(4.10)	(4.29)
Election x Exposed x Connected	-12.1	-12.2	-12.3
	(-1.50)	(-1.51)	(-1.51)
PostElection			29.2***
			(4.33)
PostElection x Exposed			32.1***
			(4.31)
PostElection x Exposed x Connected			-10.1
			(-1.37)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	486,413	486,413	542,956
R-squared adj.	0.697	0.701	0.707

Table 2.A2: The Effect of Sensitivity, Narrower *Election* and *PostElection* Period

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7), using a narrower *Election* and *PostElection* period. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-8, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+8]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*			
	(1)	(2)	(3)	(4)
Election	5.12***	5.33***	5.11***	5.45***
	(3.38)	(3.51)	(3.53)	(3.71)
Election x Sensitive	7.05***	7.26***	7.04***	7.37***
	(4.45)	(4.57)	(4.61)	(4.76)
PostElection			3.82***	3.57***
			(3.61)	(3.65)
Post x Sensitive			5.61***	5.26***
			(4.41)	(4.48)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	691,340	691,340	737,650	737,650
R-squared adj.	0.841	0.842	0.841	0.843
	Panel B: *LSKEW (%, p.a.)*			
Election	0.75**	0.54*	0.74**	0.55**
	(2.11)	(1.95)	(2.12)	(2.01)
Election x Sensitive	1.56***	1.35***	1.56***	1.37***
	(3.64)	(4.24)	(3.68)	(4.27)
PostElection			0.30	0.42**
			(1.44)	(2.02)
Post x Sensitive			0.77***	0.97***
			(2.91)	(3.63)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	691,340	691,340	737,650	737,650
R-squared adj.	0.295	0.303	0.295	0.302
	Panel C: *OIEXRET (bps, per month)*			
Election	37.0***	38.8***	36.9***	39.7***
	(2.91)	(3.01)	(3.02)	(3.18)
Election x Sensitive	54.8***	56.5***	54.8***	57.4***
	(4.10)	(4.19)	(4.20)	(4.36)
PostElection			23.1***	21.0***
			(3.06)	(3.06)
Post x Sensitive			39.7***	36.9***
			(4.44)	(4.55)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	661,710	661,710	706,014	706,014
R-squared adj.	0.724	0.726	0.724	0.728

Table 2.A3: The Effect of Sensitivity, Only Pre-Election Benchmark Period

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7), using a pre-election only benchmark period. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the interval [*d*-119, *d*-60] only. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

		Panel A: ***ATM (%, p.a.)***		
	(1)	(2)	(3)	(4)
Election	6.68***	6.68***	6.64***	6.68***
	(5.03)	(5.02)	(5.82)	(5.79)
Election x Sensitive	10.12***	10.10***	10.11***	10.16***
	(7.09)	(7.06)	(7.82)	(7.80)
PostElection			5.24***	5.01***
			(4.54)	(4.54)
Post x Sensitive			10.13***	9.72***
			(7.35)	(7.26)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	452,887	452,887	545,796	545,796
R-squared adj.	0.849	0.853	0.833	0.835
		Panel B: ***LSKEW (%, p.a.)***		
Election	0.90***	0.88***	0.89***	0.87***
	(3.72)	(4.01)	(3.88)	(4.31)
Election x Sensitive	1.22***	1.19***	1.23***	1.20***
	(3.68)	(4.41)	(3.78)	(4.56)
PostElection			0.57***	0.68***
			(2.96)	(3.66)
Post x Sensitive			0.95***	1.16***
			(3.33)	(4.38)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	452,887	452,887	545,796	545,796
R-squared adj.	0.362	0.371	0.337	0.345
		Panel C: ***OIEXRET (bps, per month)***		
Election	46.7***	46.8***	46.5***	46.9***
	(4.55)	(4.55)	(5.15)	(5.17)
Election x Sensitive	72.1***	72.2***	72.0***	72.5***
	(6.32)	(6.31)	(6.79)	(6.89)
PostElection			38.8***	36.6***
			(4.86)	(4.92)
Post x Sensitive			67.6***	64.1***
			(6.88)	(6.88)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	432,709	432,709	521,390	521,390
R-squared adj.	0.710	0.711	0.689	0.697

Table 2.A4: The Effect of Sensitivity, Accounting for Macroeconomic Uncertainty

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level, having included the Macroeconomic Uncertainty Index of Jurado et al. (2015) in the regression model. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: ***ATM (%, p.a.)***			
	(1)	(2)	(3)	(4)
Election	5.82***	5.86***	5.80***	5.88***
	(5.39)	(5.43)	(5.89)	(5.87)
Election x Sensitive	2.79***	2.86***	2.79***	2.91***
	(3.18)	(3.26)	(3.36)	(3.45)
PostElection			4.42***	4.21***
			(4.49)	(4.52)
Post x Sensitive			2.98***	2.88***
			(3.38)	(3.46)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	732,221	732,221	817,369	817,369
R-squared adj.	0.839	0.840	0.838	0.841
	Panel B: ***LSKEW (%, p.a.)***			
Election	0.96***	0.92***	0.95***	0.92***
	(4.23)	(4.68)	(4.32)	(4.85)
Election x Sensitive	0.58***	0.52***	0.58***	0.53***
	(2.65)	(2.74)	(2.71)	(2.81)
PostElection			0.63***	0.72***
			(3.50)	(4.34)
Post x Sensitive			0.42**	0.48**
			(2.01)	(2.33)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	732,221	732,221	817,369	817,369
R-squared adj.	0.295	0.302	0.295	0.303
	Panel C: ***OIEXRET (bps, per month)***			
Election	39.2***	39.7***	39.1***	39.8***
	(4.22)	(4.26)	(4.54)	(4.58)
Election x Sensitive	26.1***	26.8***	26.1***	27.1***
	(3.39)	(3.46)	(3.55)	(3.66)
PostElection			30.7***	28.8***
			(4.20)	(4.23)
Post x Sensitive			24.2***	23.4***
			(3.59)	(3.73)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	698,977	698,977	780,189	780,189
R-squared adj.	0.714	0.717	0.712	0.719

Table 2.A5: The Effect of Sensitivity, Accounting for Market Volatility

This Table shows the coefficient estimates for alternative specifications of the regression model (2.7). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty index of Baker et al. (2016) is significant at the 10% level, having included the S&P 500 VIX Index in the regression model. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*			
	(1)	(2)	(3)	(4)
Election	6.00***	6.05***	5.99***	6.07***
	(5.35)	(5.38)	(5.85)	(5.83)
Election x Sensitive	1.17**	1.23**	1.17**	1.26**
	(2.06)	(2.15)	(2.09)	(2.22)
PostElection			4.60***	4.39***
			(4.49)	(4.53)
Post x Sensitive			1.36**	1.27**
			(2.36)	(2.30)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	732,221	732,221	817,369	817,369
R-squared adj.	0.839	0.840	0.838	0.840
	Panel B: *LSKEW (%, p.a.)*			
Election	0.99***	0.95***	0.98***	0.95***
	(4.26)	(4.77)	(4.36)	(4.95)
Election x Sensitive	0.30*	0.26	0.31*	0.26
	(1.72)	(1.55)	(1.76)	(1.59)
PostElection			0.65***	0.74***
			(3.56)	(4.40)
Post x Sensitive			0.22	0.27
			(1.22)	(1.49)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	732,221	732,221	817,369	817,369
R-squared adj.	0.2944	0.302	0.2951	0.303
	Panel C: *OIEXRET (bps, per month)*			
Election	40.8***	41.4***	40.8***	41.5***
	(4.22)	(4.27)	(4.54)	(4.58)
Election x Sensitive	12.6**	13.1***	12.6***	13.4***
	(2.55)	(2.63)	(2.61)	(2.73)
PostElection			32.2***	30.3***
			(4.23)	(4.29)
Post x Sensitive			11.9***	11.1***
			(2.61)	(2.58)
Controls	No	Yes	No	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	698,977	698,977	780,189	780,189
R-squared adj.	0.714	0.717	0.712	0.718

Table 2.A6: The Effect of Political Exposure, Alternative Definition of Republican President Dummy

This Table shows the coefficient estimates for alternative specifications of the regression models (2.8) and (9). The dummy variables *Election* and *PostElection* are defined in Table 3. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level, but now the Republican President dummy takes the value 1 from August prior to the election of a Republican Presidential candidate and the value 0 from August prior to the election of a Democrat Presidential candidate. The dummy variables *Exposed_Incumbent*(*Contender*) and *Exposed_Winner*(*Loser*) are defined in Table 3. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

			Panel A: ***ATM (%, p.a.)***			
	(1)	(2)	(3)	(4)	(5)	(6)
Election	6.14***	6.20***	6.20***	6.12***	6.21***	6.21***
	(5.59)	(5.62)	(5.62)	(6.10)	(6.06)	(6.06)
Election x Exposed	2.92***	2.96***		2.92***	2.98***	
	(3.73)	(3.79)		(3.92)	(3.97)	
Election x			3.83***			3.85***
Exposed_Incumbent			(3.30)			(3.41)
Election x			1.71**			1.72**
Exposed_Contender			(2.24)			(2.40)
PostElection				4.64***	4.43***	4.43***
				(4.64)	(4.69)	(4.69)
PostElection x Exposed				3.29***	3.15***	
				(4.07)	(4.10)	
PostElection x						0.26
Exposed_Winner						(0.44)
PostElection x						6.83***
Exposed_Loser						(5.53)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	509,008	568,231	568,231	568,231
R-squared adj.	0.827	0.829	0.829	0.828	0.830	0.831

			Panel B: ***LSKEW (%, p.a.)***			
Election	0.97***	0.93***	0.93***	0.97***	0.93***	0.93***
	(3.98)	(4.39)	(4.39)	(4.08)	(4.57)	(4.57)
Election x Exposed	0.55***	0.53***		0.55***	0.53***	
	(2.86)	(3.17)		(2.87)	(3.17)	
Election x			0.77***			0.76***
Exposed_Incumbent			(3.51)			(3.49)
Election x			0.18			0.20
Exposed_Contender			(0.78)			(0.92)
PostElection				0.73***	0.82***	0.82***
				(3.79)	(4.52)	(4.52)
PostElection x Exposed				0.27	0.34**	
				(1.55)	(2.05)	
PostElection x						0.19
Exposed_Winner						(0.95)
PostElection x						0.52**
Exposed_Loser						(2.00)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	509,008	509,008	509,008	568,231	568,231	568,231
R-squared adj.	0.305	0.312	0.313	0.304	0.312	0.312

Table 2.A6: (Continued)

	Panel C: *OIEXRET (bps, per month)*					
Election	40.9***	41.4***	41.4***	40.8***	41.5***	41.5***
	(4.32)	(4.36)	(4.36)	(4.64)	(4.67)	(4.67)
Election x Exposed	25.9***	26.3***		25.9***	26.5***	
	(3.89)	(3.95)		(4.04)	(4.13)	
Election x			35.8***			35.6***
Exposed_Incumbent			(3.63)			(3.71)
Election x			12.8**			13.3**
Exposed_Contender			(2.15)			(2.36)
PostElection				31.5***	29.6***	29.6***
				(4.27)	(4.33)	(4.33)
PostElection x Exposed				24.4***	23.2***	
				(4.12)	(4.21)	
PostElection x						2.7
Exposed_Winner						(0.68)
PostElection x						50.2***
Exposed_Loser						(5.26)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	486,413	486,413	486,413	542,956	542,956	542,956
R-squared adj.	0.697	0.701	0.701	0.699	0.707	0.707

Table 2.A7: The Effect of Political Connectedness, Alternative Definition of Connectedness I

This Table shows the coefficient estimates for alternative specifications of the regression model (2.12), using a different definition for a firm to be connected (*Connected**). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Connected** is a dummy variable that takes the value 1 for a firm if the number of US Congress, Senate, or Presidential candidates that its PAC has contributed money to during the past 60 months is higher than the corresponding cross-sectional median across firms with positive contributions. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: ***ATM (%, p.a.)***		
	(1)	(2)	(3)
Election	6.04***	6.10***	6.12***
	(5.37)	(5.41)	(5.84)
*Election x Connected**	0.48	0.48	0.47
	(1.10)	(1.10)	(1.09)
PostElection			4.29***
			(4.47)
*PostElection x Connected**			1.44***
			(3.11)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	817,579
R-squared adj.	0.839	0.840	0.840
	Panel B: ***LSKEW (%, p.a.)***		
Election	0.95***	0.90***	0.90***
	(4.08)	(4.66)	(4.78)
*Election x Connected**	0.48**	0.48**	0.48**
	(2.40)	(2.41)	(2.53)
PostElection			0.69***
			(4.11)
*PostElection x Connected**			0.53***
			(2.59)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	817,579
R-squared adj.	0.294	0.302	0.303
	Panel C: ***OIEXRET (bps, per month)***		
Election	42.7***	43.3***	43.4***
	(4.28)	(4.33)	(4.64)
*Election x Connected**	-4.1	-4.1	-4.2
	(-1.40)	(-1.40)	(-1.41)
PostElection			31.2***
			(4.33)
*PostElection x Connected**			0.9
			(0.32)
Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	699,165	699,165	780,399
R-squared adj.	0.714	0.717	0.718

Table 2.A8: The Effect of Political Connectedness, Alternative Definition of Connectedness II

This Table shows the coefficient estimates for alternative specifications of the regression model (2.12), using a different definition for a firm to be connected (*Connected_HQState*). *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. *Connected_HQState* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money during the past 60 months to the PAC of a US Congress or Senate candidate who has also been elected in the state of the firm's headquarters. *Num. of Connections_HQState* denotes the number of candidates that the firm PAC has contributed to and have been elected in the state of the firm's headquarters. *ATM*, *LSKEW*, and *OIEXRET* are defined in Table 1. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: *ATM (%, p.a.)*			
	(1)	(2)	(3)	(4)
Election	6.08***	6.14***	6.19***	6.16***
	(5.38)	(5.42)	(5.44)	(5.85)
Election x Connected_HQState	0.14	0.13		0.12
	(0.39)	(0.38)		(0.35)
Election x ln(1+Num. of Connections_HQState)			-0.03	
			(-0.20)	
PostElection				4.28***
				(4.42)
PostElection x Connected_HQState				0.86**
				(2.50)
Controls	No	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	732,409	815,579
R-squared adj.	0.839	0.840	0.840	0.840

	Panel B: *LSKEW (%, p.a.)*			
Election	0.92***	0.88***	0.88***	0.88***
	(4.00)	(4.59)	(4.56)	(4.69)
Election x Connected_HQState	0.35**	0.35**		0.35**
	(2.35)	(2.40)		(2.50)
Election x ln(1+Num. of Connections_HQState)			0.17**	
			(2.50)	
PostElection				0.69***
				(4.10)
PostElection x Connected_HQState				0.30*
				(1.86)
Controls	No	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	732,409	732,409	732,409	817,579
R-squared adj.	0.294	0.302	0.302	0.303

Table 2.A8: (Continued)

	Panel C: *OIEXRET (bps, per month)*			
Election	43.1***	43.7***	44.2***	43.9***
	(4.29)	(4.33)	(4.35)	(4.65)
Election x Connected_HQState	-4.0	-4.0		-4.1
	(-1.59)	(-1.60)		(-1.61)
Election x ln(1+Num. of Connections_HQState)			-2.8**	
			(-2.51)	
PostElection				31.6***
				(4.35)
PostElection x Connected_HQState				-0.9
				(-0.40)
Controls	No	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day	Firm-Cycle&Day
Observations	699,165	699,165	699,165	780,399
R-squared adj.	0.714	0.717	0.717	0.718

Table 2.A9: The Effect on Option Total Open Interest

This Table shows the coefficient estimates from regression models where the dependent variable is the daily total open interest (*TOTOI*) of options with expiry between 16 and 60 days ahead. *TOTOI* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (2.7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (2.8) and (2.9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (2.12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression model (2.10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				**Panel C: Connectedness**		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.256***	0.257***	0.257***	*Election*	0.269***	0.270***	0.271***
	(4.62)	(4.64)	(4.65)		(4.76)	(4.79)	(4.80)
Election x Sensitive	0.035	0.036	0.038	*Election x Connected*	-0.032	-0.032	-0.031
	(0.54)	(0.57)	(0.58)		(-0.89)	(-0.89)	(-0.89)
PostElection			-0.085	*PostElection*			-0.100
			(-1.15)				(-1.43)
PostElection x Sensitive			0.010	*PostElection x Connected*			0.051
			(0.13)				(1.29)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	708,394	708,394	790,767	Observations	708,394	708,394	790,767
R-squared adj.	0.361	0.362	0.362	R-squared adj.	0.361	0.362	0.362

Table 2.A9: (Continued)

	Panel B: Exposure				Panel D: Alignment		
Election	0.261***	0.261***	0.261***	*Election*	0.265***	0.244***	0.244***
	(4.52)	(4.52)	(4.52)		(4.66)	(4.16)	(4.18)
Election x Exposed	0.013	0.015		*Election x*	0.063	0.084**	0.087**
	(0.22)	(0.24)		*Aligned_Incumbent*	(1.60)	(2.02)	(2.19)
Election x Exposed_Incumbent			0.079	*Election x*		0.062	0.061
			(0.98)	*Aligned_Contender*		(1.54)	(1.58)
Election x Exposed_Contender			-0.069	*PostElection*			-0.084
			(-0.88)				(-1.08)
PostElection		-0.071	-0.071	*PostElection x*			0.017
		(-0.89)	(-0.89)	*Aligned_Winner*			(0.43)
PostElection x Exposed		-0.034		*PostElection x*			0.021
		(-0.53)		*Aligned_Loser*			(0.59)
PostElection x			-0.151**				
Exposed_Winner			(-2.27)				
PostElection x Exposed_Loser			0.126				
			(1.24)				
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	498,238	556,201	556,201	Observations	775,653	775,653	865,852
R-squared adj.	0.361	0.362	0.362	R-squared adj.	0.374	0.374	0.376

Table 2.A10: The Effect on the Ratio of Option-to-Stock Trading Volume

This Table shows the coefficient estimates from regression models where the dependent variable is the daily ratio of option-to-stock trading volume (*TOTVOL-to-STOCKVOL*) using options with expiry between 16 and 60 days. *TOTVOL-to-STOCKVOL* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (2.7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (2.8) and (2.9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (2.12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression model (2.10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				**Panel C: Connectedness**		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.236***	0.236***	0.236***	*Election*	0.246***	0.246***	0.246***
	(4.05)	(4.05)	(4.05)		(4.09)	(4.09)	(4.09)
Election x Sensitive	-0.007	-0.006	-0.006	*Election x Connected*	-0.034	-0.034	-0.034
	(-0.13)	(-0.11)	(-0.11)		(-1.08)	(-1.09)	(-1.08)
PostElection			-0.184***	*PostElection*			-0.195***
			(-3.41)				(-3.51)
PostElection x Sensitive			-0.083*	*PostElection x Connected*			0.009
			(-1.72)				(0.32)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	708,393	708,393	790,766	Observations	708,393	708,393	790,766
R-squared adj.	0.090	0.090	0.091	R-squared adj.	0.090	0.090	0.091

Table 2.A10: (Continued)

	Panel B: Exposure		
Election	0.228***	0.228***	0.228***
	(3.56)	(3.56)	(3.56)
Election x Exposed	-0.028	-0.027	
	(-0.58)	(-0.57)	
Election x Exposed_Incumbent			0.050
			(0.78)
Election x Exposed_Contender			-0.126**
			(-2.02)
PostElection		-0.201***	-0.201***
		(-3.48)	(-3.48)
PostElection x Exposed		0.035	
		(0.83)	
PostElection x Exposed_Winner			-0.004
			(-0.08)
PostElection x Exposed_Loser			0.089
			(1.45)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	498,237	556,200	556,200
R-squared adj.	0.088	0.088	0.088

	Panel D: Alignment		
Election	0.213***	0.207***	0.205***
	(3.72)	(3.46)	(3.45)
Election x Aligned_Incumbent	0.058*	0.064*	0.070**
	(1.69)	(1.80)	(2.02)
Election x Aligned_Contender		0.019	0.019
		(0.60)	(0.58)
PostElection			-0.213***
			(-3.72)
PostElection x Aligned_Winner			0.040
			(1.19)
PostElection x Aligned_Loser			0.017
			(0.53)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	775,652	775,652	865,851
R-squared adj.	0.091	0.091	0.092

Table 2.A11: The Effect on the Ratio of Out-of-The-Money Puts-to-Total Option Trading Volume

This Table shows the coefficient estimates from regression models where the dependent variable is the daily ratio of trading volumes of out-of-the-money puts to all options (*OTMPUTVOL-to-TOTVOL*) with expiry between 16 and 60 days. *OTMPUTVOL-to-TOTVOL* is normalized to be expressed as a multiple of the corresponding firm-level average daily value computed from January to June prior to the November Presidential Election. *Election* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*-15, *d*-1], where *d* is the US Presidential Election day from 1996 to 2016. *PostElection* is a dummy variable that takes the value 1 for the calendar days in the interval [*d*+1, *d*+15]. The benchmark period is the union of the intervals [*d*-119, *d*-60] and [*d*+61, *d*+120]. Panel A shows the coefficient estimates for alternative specifications of the regression model (2.7). *Sensitive* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Economic Policy Uncertainty Index of Baker et al. (2016) is significant at the 10% level. Panel B shows the coefficient estimates for alternative specifications of the regression models (2.8) and (2.9). *Exposed* is a dummy variable that takes the value 1 for a firm if the regression slope coefficient estimate of its stock return on the Republican President dummy is significant at the 10% level. *Exposed_Incumbent*(*Contender*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican President is in office or negative (positive) when a Democrat President is in office. *Exposed_Winner*(*Loser*) is a dummy variable that takes the value 1 if the sign of this significant slope coefficient is positive (negative) when a Republican Presidential candidate has been elected or negative (positive) when a Democrat Presidential candidate has been elected. Panel C shows the coefficient estimates for alternative specifications of the regression model (2.12). *Connected* is a dummy variable that takes the value 1 for a firm if its PAC has contributed money to the PAC of a US Congress, Senate, or Presidential candidate during the past 60 months. Panel D shows the coefficient estimates for alternative specifications of the regression model (2.10). *Aligned_Incumbent*(*Contender*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI before the election. *Aligned_Winner*(*Loser*) is a dummy variable that takes the value 1 for a firm if its headquarters are located in one of the top (bottom) quartile states according to PAI right after the election. Control variables include the daily stock and market returns. Standard errors are two-way clustered at the firm-by-cycle & day levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Sensitivity				Panel C: Connectedness		
	(1)	(2)	(3)		(1)	(2)	(3)
Election	0.137***	0.135***	0.135***	*Election*	0.129***	0.128***	0.127***
	(5.11)	(5.12)	(5.10)		(4.57)	(4.58)	(4.57)
Election x Sensitive	-0.020	-0.022	-0.022	*Election x Connected*	0.018	0.018	0.018
	(-0.41)	(-0.46)	(-0.45)		(0.59)	(0.58)	(0.57)
PostElection			0.003	*PostElection*			-0.031
			(0.13)				(-1.21)
PostElection x Sensitive			0.019	*PostElection x Connected*			0.117***
			(0.37)				(3.71)
Controls	No	Yes	Yes	Controls	No	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle	Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day	Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	699,885	699,885	781,259	Observations	699,885	699,885	781,259
R-squared adj.	0.051	0.051	0.051	R-squared adj.	0.051	0.051	0.051

Table 2.A11: (Continued)

Panel B: Exposure			
Election	0.131***	0.131***	0.131***
	(4.65)	(4.62)	(4.62)
Election x Exposed	-0.005	-0.005	
	(-0.10)	(-0.09)	
Election x Exposed_Incumbent			0.027
			(0.42)
Election x Exposed_Contender			-0.045
			(-0.64)
PostElection		0.026	0.026
		(0.97)	(0.97)
PostElection x Exposed		0.018	
		(0.36)	
PostElection x Exposed_Winner			-0.022
			(-0.35)
PostElection x Exposed_Loser			0.074
			(1.03)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	491,974	549,201	549,201
R-squared adj.	0.05	0.051	0.051

Panel D: Alignment			
Election	0.125***	0.114***	0.114***
	(4.63)	(3.81)	(3.81)
Election x Aligned_Incumbent	0.010	0.021	0.026
	(0.29)	(0.59)	(0.76)
Election x Aligned_Contender		0.033	0.029
		(0.92)	(0.83)
PostElection			-0.000
			(-0.01)
PostElection x Aligned_Winner			0.011
			(0.31)
PostElection x Aligned_Loser			-0.021
			(-0.62)
Controls	Yes	Yes	Yes
Fixed Effects	Firm-Cycle	Firm-Cycle	Firm-Cycle
Clusters	Firm-Cycle & Day	Firm-Cycle & Day	Firm-Cycle & Day
Observations	766,674	766,674	855,819
R-squared adj.	0.050	0.050	0.051

Chapter 3

Is the term structure of the S&P 500 risk-neutral Cumulants priced in the cross section of equity returns?

3.1 Introduction

Asset pricing is about identifying factors which price the cross section of expected returns. To this end, index options may be useful, because their forward looking market prices may reveal the expectations of informed investors (see, for example, Black (1975); Easley et al. (1998)). The previous literature has examined whether asset pricing factors can be constructed from the risk-neutral moments (RNMs) of the Standard & Poor's (S&P) 500 index returns distribution. These studies motivate the construction of the factors within Merton's (1973) Intertemporal Capital Asset Pricing model (ICAPM) setting, and they use either single maturity RNMs (Ang, Hodrick, Xing, and Zhang (2006); Chang, Christoffersen, and Jacobs (2013)), or a synopsis of the term structure of the second RNM (Xie (2014); Dotsis (2017)) as pricing factors. A key implicit assumption, is that RNMs proxy the physical moments, and thus they are related to the investment opportunity set[1]. Hence, under the ICAPM setting, the RNMs are used as state variables, and their innovations are used as factors.

However, the assumption that physical moments can be proxied by their risk-neutral counterparts is debatable (see, e.g., Bliss and Panigirtzoglou (2004)). In addition, the evidence on whether these factors are priced is weak in light of the recent literature, which suggests using greater critical values for t-statistics to assess the statistical significance of results in order to alleviate concerns on data mining (e.g, Hou, Xue, and Zhang, 2015; Harvey, Liu, and Zhu, 2016).

We revisit this literature, by taking an alternative approach to identify state variables, that circumvents the assumption about the relation between physical and risk-neutral moments. In the theoretical setting of Feunou, Fontaine, Taamouti, and Tédongap (2014), the vector of state variables is an affine function of the term structure of any given order's risk-neutral cumulant (RNCs; non-normalised RNMs) of the return's distribution of a claim on aggregate consumption. Furthermore, the stochastic discount factor (SDF) is an affine function of the levels, rather than the innovations, of the state variables. Hence, in contrast to the previous literature, we use the levels of the RNCs of the S&P 500 returns distribution, rather than the innovations of its RNMs, to identify factors of risk.

First, we estimate the unobserved linear combination of RNC maturities, by applying three alternative dimensionality reduction techniques (DRTs) to the term structure of any given order's RNC: (i) the principal component analysis (PCA), (ii) the three pass regression filter of Kelly and Pruitt (3PRF, 2015), and (iii) the reduced rank regression (RRR) analysis. The last two DRTs construct affine factors, which also take into account the fundamental relation between the market risk premium and the vector of the state variables, as dictated by the Feunou

[1] Xie (2014) employs an alternative approach. He relates the slope of the VIX term structure to the investment opportunity set, within an extension of Gabaix's (2012) rare disaster model.

et al. (2014) setting. Subsequently, we test whether the constructed factors are priced in the cross section of stock returns. Furthermore, as a special case of a linear combination of RNCs with different maturities, we also examine the pricing performance of a single horizon RNC. This corresponds to the linear combination of an RNC term structure, where the weights of the other horizons, but the employed one, are zero. Finally, to examine whether our results may be driven by the Feunou et al. (2014) setting, we test the pricing performance of each factor in an ICAPM setting. We do this, by testing whether its innovations are priced in the cross section of stock returns.

We apply each DRT to the term structure of the 2^{nd}, 3^{rd}, and 4^{th} RNC of the S&P 500 index returns distribution, separately, for the period spanning January 1996 to December 2017. We find that at most two factors explain the dynamics of the term structure of RNCs for any given order's RNC term structure. The PCA reveals that the first principal component (PC) affects RNCs roughly the same across their maturities (level interpretation), whereas the second PC affects positively (negatively) the shorter (longer) RNC maturities, thus it has a slope interpretation. The two factors obtained from RRR are correlated with the two respective PC factors, whereas the factor obtained from 3PRF is correlated with the second PC factor. These findings hold regardless of the order of the examined RNC. To test the pricing performance of each factor, we conduct two types of exercises. First, we estimate the price of risk of each factor, by means of rolling window and full sample Fama and MacBeth (FM, 1973) regressions. To assess the robustness of the results, we employ different sizes for the rolling window and alternative sets of test portfolios. Second, we sort all stocks traded in NYSE, NASDAQ, and Amex, in portfolios based on the beta exposure of each stock returns to any given factor. Subsequently, we examine whether the spread portfolio, that is long the portfolio containing the stocks with the highest betas and short the portfolio containing the stocks with the lowest betas, yields a significant performance, as well as whether there is a monotonic relation between the average returns of the sorted portfolios and the factor's exposure. For robustness, we estimate the factor exposure (beta) by using different sizes for the estimation window, and we perform the analysis by sorting stocks in decile and quintile portfolios, separately.

The FM regressions yield that factors which use information from the term structure of RNCs are not priced. The price of risk of any given factor is either insignificant or not robustly significant across the different test assets, and the different lengths of the rolling windows. The results hold regardless of the order of examined RNCs. Hence, our findings imply that the term structure of any given order's RNC does not contain useful information to construct factors of risk that price the cross section of stock returns. The portfolio sorting exercises yield similar results to the FM regressions. We do not observe a linear monotonic relationship between the factor exposure of the constructed portfolios and their average returns. Furthermore, the return of the spread portfolio is either insignificant or not robustly significant across the different beta estimation windows.

The fact that factors are found to be non priced in the cross section of our test assets, implies that the term structure of RNCs does not contain useful information for asset pricing purposes. It may be the case though that RNCs of specific maturities does contain such useful information. Hence, we repeat the asset pricing tests by considering RNCs of single maturities of one, three, six, and twelve months as respective potential factors. Again, we find that the factors constructed as single RNC maturities are not priced.

Our findings on the non pricing performance of constructed factors, may also be a manifestation that the Feunou et al. (2014) setting is misspecified, rather than genuinely indicating that the term structure of RNCs contains no information to construct asset pricing factors. To address this point, we repeat the asset pricing tests by considering the innovations rather than the levels of our factors. This representation bypasses the Feunou et al. (2014) setting, is consistent with an ICAPM setting, and makes our analysis directly comparable to the studies of Ang et al. (2006) and Chang et al. (2013). Again, we find that the innovations of our factors are not priced in the cross section of stock returns. Our paper contributes to the literature which investigates whether index option prices may contain information that can be used to construct factors to price stock returns. The most related studies to ours are the ones by Ang et al. (2006), Chang et al. (2013), Xie (2014), and Dotsis (2017), who use option prices written on the S&P 500 index to extract systemic factors of risk. The empirical evidence is mixed and at best weak, given the recent literature which suggests using critical values of 3 for the t-test statistics to evaluate the significance of the pricing performance of factors, to alleviate data mining concerns (Harvey et al., 2016).

In particular, in their benchmark analysis Ang et al. (2006) use daily returns over one month to estimate the stocks' exposure to the innovations of aggregate volatility, proxied by the Chicago Board Options Exchange Volatility Index (VIX). They find that the spread portfolio, that is long the portfolio containing the stocks with the highest exposures and short the portfolio containing the stocks with the lowest exposures, yields a statistically significant negative alpha equal to approximately -1% (t-stat = -3.04) per annum during the 1986-2000 period. In contrast, Chang et al. (2013) follow the same procedure and find that the price of risk of Risk-Neutral Volatility, essentially identical to VIX, is statistically indistinguishable to zero during the 1996-2007 period. In our study, we find that the innovations of RNV (square of Risk-Neutral Volatility) are not priced during the 1996-2017 period. In untabulated results, we have also tested whether the innovations of Risk-Neutral Volatility are priced during the 1996-2017 period. We confirm that the result of Chang et al. (2013) in our extended sample period. Chang et al. (2013) also apply the same analysis to estimate the price of risk for the innovations of RNS. They find that the spread portfolio earns on average a monthly

Fama-French-Carhart alpha equal to -0.80% (t-stat = -2.42) during the 1996-2007 period. In untabulated results, we repeat their exercise and document an alpha equal to -0.61% (t-stat = -2.02), which is quantitatively and statistically comparable. In our extended sample, though, ranging from 1996 to 2017 the alpha of the spread portfolio is statistically indistinguishable to zero. Finally, in their benchmark analysis, Xie (2014) and Dotsis (2017) employ different empirical approaches to the one used by Ang et al. (2006). Xie (2014) uses a trivariate portfolio sorting procedure that controls for the market return and the level of the VIX term-structure. He documents that the innovations of the slope of the VIX term-structure earn a positive price of risk of approximately 2.5% (t-stat = 2.31) per annum during the 1996-2013 period. Dotsis (2017) uses a 5-year rolling-window to estimate the stocks' exposures to the innovations of the RNV term-structure using monthly rather than daily returns. In contrast to Xie (2014), he finds that the spread portfolio earns a negative price of risk approximately equal to -5% (t-stat = 2.05) per annum during the 1996-2013 period. He does not, though, document a monotonic relation between the factor exposure of the constructed portfolio and their average returns. We have not attempted to replicate their results. We use different variations of the methodology followed by Ang et al. (2006) and find that the price of risk for the innovation of the slope of the RNV term-structure is not priced during the 1996-2017 period.

Our contribution to this strand of literature surpasses the mere replication of previous studies. Our paper differs from the aforementioned ones in three ways. First, our empirical approach is founded theoretically. Instead of conjecturing that RNMs proxy for unobserved state variables by resorting in an ICAPM setting, we utilise the arguments of Feunou et al. (2014) that theoretically predict that the state variables are a linear combination of the *levels* of the RNCs.[2] Second, we investigate whether factors constructed from the term structures of RNCs of various orders, separately, price the cross section of equity returns. Previous studies have examined only the term structure of the RNV (second RNC). Third, in addition to the PCA that has been used by the previous studies to extract risk factors from the term structure of the S&P 500 option prices, we also employ two alternative DRTs. These construct factors by respecting the fundamental relation between the market risk premium and state variables; PCA does not share this desirable theoretical property.

More generally, our paper contributes to the literature which proposes factors for asset pricing.[3] The provided evidence that the term structure of RNCs is not priced in the cross-section of stock returns may be due to the fact that either the Feunou et al. (2014) setting is not valid, and/or factors are mis-estimated, and/or constructed factors are indeed not priced. Given that the affine setting is a well accepted paradigm (e.g., see Duffie, Pan, and Singleton, 2000, and references therein), and that our results hold regardless of the method we use to construct factors, our findings echo the more recent evidence that most of the asset pricing anomalies documented by the previous literature do not hold (Hou, Xue, and Zhang (2018)). This new evidence is attributed to the more conservative critical values used to assess significance, the formation of portfolios in the portfolio sorts analysis to minimize the effect of micro-cap stocks (value weighted instead of equally weighted), and the longer time periods being examined. Our study employs all three dimensions.

[2]Maio and Santa-Clara (2012) show that the ICAPM should not be blindly used as a fishing license to justify the use of certain factors for asset pricing purposes. Instead, certain conditions should be satisfied, including the presence of a theoretical background.

[3]Some notable examples of this literature are the market return of Sharpe (1964) and Lintner (1965), the squared market return of Kraus and Litzenberger (1976), the consumption growth of Breeden (1979), the size and book-to-market factors of the Fama and French (1992) model, the return momentum of Carhart (1997), the market liquidity of Pastor and Stambaugh (2003), and the market trading volume of Lo and Wang (2006).

Our study should not be viewed as complementary to the growing literature that utilizes information embedded in option prices written on *individual* stocks to predict future stock returns, such as (Cremers and Weinbaum (2010), Rehman and Vilkov (2012), Bali and Murray (2013), Conrad et al. (2013), Stilger et al. (2017), Gkionis et al. (2018), and Wang (2017)). According to the factor taxonomy of Harvey et al. (2016), these studies employ individual firm characteristics that lead to predictive relations which cannot be justified by the established asset pricing models (asset pricing anomalies). In contrast, our study complements the literature that seeks to identify "common" risk factors. As put by Harvey et al. (2016), "[w]hile the beta against the market return is systematic (exposure to a common risk factor), the standard deviation of the market model residual is not based on a common factor – it is a property of the individual firm, that is, it is an idiosyncratic characteristic."[4]

The rest of the paper is organised as follows. In Section 2, we present the setting of Feunou et al. (2014), explain how the term structure of any given order's RNC may reveal the vector of the state variables, and provide the RNCs formulae. In Section 3, we describe the data we use and the calculation of RNCs. Section 4, presents the results of the three DRTs we employ to construct factors. Sections 5 and 6 presents the results of the FM regressions and of the portfolio sorts, respectively. Section 7, presents the results on the pricing performance of the innovations of each constructed factor, and the pricing performance of RNS in our sample. Section 7 concludes and discusses the findings.

[4]The studies on the use of the informational content of equity options for asset pricing purposes, in line with Cremers and Weinbaum (2010), document that options written on individual stocks can predict subsequent stock performance. The explanation put forward lies to the limits of arbitrage, most notably short selling constraints, that a stock is subject to. In a nutshell, investors that want to short an overpriced stock and hindered to do so in the spot market due to limits of arbitrage, trade their belief in the stock's option market by buying (selling) put (call) options and thus raising (lowering) their price, in line to the demand based option pricing model of Garleanu et al. (2009). The relatively expensiveness of put options relative to call options leads to greater put-call parity violations that predict subsequent stock underperformance as the negative information that has been embedded in the option prices is slowly diffused to the spot market due to limits-of-arbitrage.

3.2 Methodology

We investigate whether the informational content of S&P 500 market options prices can be used to explain the cross sectional variability of equity returns. To this end, we employ the theoretical framework of Feunou et al. (2014). They show that in the context of affine general equilibrium models, the SDF is an affine function of the RNCs of the distribution of returns of aggregate consumption.

To fix ideas, let xr_{t+1} be the (log) excess return from holding an asset from period t to $t+1$ over the return of the (log) risk-free asset, $r_{f,t}$,

$$xr_{t+1} \equiv \log \frac{S_{t+1}}{S_t} - r_{f,t}, \tag{3.1}$$

where S_t denotes the time-t price of the asset. Feunou et al. (2014, see Appendices A.1 - A.4) consider affine models that satisfy the following three properties. (i) Excess returns, xr_{t+1}, and the vector of the K state variables, X_{t+1}, belong to the family of affine jump-diffusion continuous-time models, (ii) the risk-free rate is an affine function of X_t, and (iii) the SDF is an exponential affine function of X_{t+1} and xr_{t+1}. Moreover, they show that under these three properties, the (log) SDF factor from period t to period $t+1$ is

$$m_{t,t+1} = \theta + \gamma \, xr^e_{t+1} + \Gamma^\top X_{t+1}, \tag{3.2}$$

where θ, γ, and Γ are parameters of the underlying model and xr^e_{t+1} is the excess return from a claim on aggregate consumption. Furthermore, the cumulant-generating functions of excess returns on aggregate consumption over an investment horizon τ, $xr^e_{t,t+\tau} \equiv \sum_{j=1}^{\tau} xr^e_{t+j}$, under the physical measure, $\mathbb{P}$, and the risk-neutral measure, $\mathbb{Q}$, are given by

$$E^{\mathbb{P}}_t \left[\exp(u \, xr^e_{t,t+\tau}) \right] = \exp\left(\mathcal{F}^{\mathbb{P}}_{r,0}(u;\tau) + X_t^T \mathcal{F}^{\mathbb{P}}_{r,X}(u;\tau) \right) \tag{3.3}$$

and

$$E_t^{\mathbb{Q}}\left[\exp(u\, xr^e_{t,t+\tau})\right] = \exp\left(\mathcal{F}^{\mathbb{Q}}_{r,0}(u;\tau) + X_t^T \mathcal{F}^{\mathbb{Q}}_{r,X}(u;\tau)\right), \tag{3.4}$$

where $\mathcal{F}^{\mathbb{M}}_{r,0}(u;\tau)$ and $\mathcal{F}^{\mathbb{M}}_{r,0}(u;\tau)$ for $\mathbb{M} = \mathbb{P}, \mathbb{Q}$, are functions of the argument u, and the parameters of the underlying model. Subsequently, by taking the first derivative of the cumulant generating function under $\mathbb{P}$, in (3.3), with respect to its argument u, evaluated at $u = 0$, the equity premium over an investment horizon τ can be stated as

$$\mathrm{EP}(t,\tau) \equiv E_t^{\mathbb{P}}\left[xr^e_{t,\,t+\tau}\right] = \beta_{ep,0}(\tau) + \beta_{ep}(\tau)^\top X_t, \tag{3.5}$$

where $\beta_{ep,0}(\tau)$ and $\beta_{ep}(\tau)$ are functions of the parameters of the underlying model and the jth element of $\beta_{ep}(\tau)$, $\beta_{j,ep}(\tau)$, expresses the sensitivity of the equity premium over the horizon τ to the jth state variable, $X_{j,t}$. Moreover,the nth derivative of the cumulant-generating function under $\mathbb{Q}$, in (3.4), with respect to its argument u, evaluated at $u = 0$, yields that the computed at time-t nth RNC of excess returns over any horizon τ is also an affine function of the state vector X_t

$$\begin{aligned} M^{\mathbb{Q}}_{t,\,n}(\tau) &\equiv E_t^{\mathbb{Q}}(\tau)\left[\left(xr^e_{t,\,t+\tau} - E_t^{\mathbb{Q}}(\tau)\left[xr^e_{t,\,t+\tau}\right]\right)^n\right] \\ &= \beta_{n,0}(\tau) + \beta_n(\tau)^\top X_t, \end{aligned} \tag{3.6}$$

where $\beta_{n,0}(\tau)$ and $\beta_n(\tau)$ are functions of the parameters of the underlying model and the jth element of $\beta_n(\tau)$, $\beta_{j,n}(\tau)$, captures the sensitivity of the nth RNC of excess returns over the horizon τ to the jth state variable, $X_{j,t}$.

3.2.1 State Variables Spanned by Risk-Neutral Cumulants

Equation (3.6) shows that any given order τ-horizon RNC is an affine function of the state vector X_t. In the case where equation (3.6) can be inverted, one can express the unobservable state vector X_t as an affine function of $M^{\mathbb{Q}}_{t,n}$, which as we show in Section 3.2.2, can be estimated. In the case of an economy where X_t is a scalar, i.e. ($K = 1$), one could invert equation (3.6) as

$$X_t = -\frac{\beta_{n,0}(\tau)}{\beta_n(\tau)} + \beta_n(\tau)^{-1} M^{\mathbb{Q}}_{t,n}(\tau), \tag{3.7}$$

For economies, where the dimension of X_t is greater than one, Feunou et al. (2014) show that X_t is an affine function of the whole term structure of any given order RNC. To see this, stack the nth RNC across q different horizons $\tau = \tau_1, \tau_2, \ldots, \tau_q$, as in

$$M^{\mathbb{Q}}_{t,n} \equiv \left[M^{\mathbb{Q}}_{t,n}(\tau_1),\, M^{\mathbb{Q}}_{t,n}(\tau_2), \ldots, M^{\mathbb{Q}}_{t,n}(\tau_q)\right]^T = B_{n,0} + B_n X_t, \tag{3.8}$$

where $B_{n,0}$ is the q-vector containing the constants $\beta_{n,0}(\tau_1)$ and B_n is the $(q \times K)$ matrix that stacks the $\beta_n(\tau_i)$ vector coefficients. The jth element of the vector $\beta_n(\tau_i)$ captures the sensitivity of the nth RNC of excess returns over the horizon τ_i to the jth state variable, $X_{j,t}$. Assuming that the number of horizons is greater than the number of states ($q \geq K$), one can invert equation (3.8) and obtain a system of linear restrictions on the state variables with respect to the different horizons of the RNC, as in

$$X_t = -\bar{B}_n B_{n,0} + \bar{B}_n M^{\mathbb{Q}}_{t,n} \tag{3.9}$$

where the $(K \times q)$ matrix, $\bar{B}_n = (B_n B_n^\top)^{-1} B_n^\top$, is the left-inverse of B_n, has a rank less or equal to K, and its element in the jth row and ith column is the sensitivity of the jth state variable, $X_{j,t}$, to the nth RNC with horizon τ_i, $M^{\mathbb{Q}}_{t,n}(\tau_i)$.[5]

[5]In our empirical analysis, we employ six different horizons. The most popular empirical asset pricing models implicitly assume that at most six state variables drive equity returns; see, e.g., the Fama and French (1996, 2015) three and five factor models, the four factor models of Carhart (1997), Novy-Marx (2013) and Hou et al. (2015). These factors are not necessarily orthogonal with each other, so possibly an even smaller number of orthogonal state variables might drive equity returns. In fact, Clarke (2016) performs Principal Component Analysis on the cross-section of equity returns and finds that three factors are sufficient to explain the cross-sectional variability of equity returns and that an asset pricing model consisting of these factors is comparable to the aforementioned models. Finally, DeMiguel, Martin-Utrera, Nogales, and Uppal (2019) simultaneously test the asset pricing performance of 23 characteristics and find

Equation (3.9) shows that the vector of state variables X_t is a linear combination of the various maturities of a given order RNC. Any technique to reduce dimensionality, amounts to constructing factors which are a linear combination of the original variables to which the technique is applied. Therefore, applying a dimensionality reduction technique (DRT) to the term structure of a given order RNC, will yield factors as linear combinations of the RNC's term structure. Hence, the derived factors could be regarded as proxies of the state variables described in equation (3.9).

A remark is in order at this point. In the case that the factors are not found to price the cross section of equity returns, this would imply that either (i) index options do not contain useful information to price equity returns, and/or (ii) the theoretical setting of affine models as developed by Feunou et al. (2014) is not valid, and/or (iii) the constructed factors are not valid proxies of the state variables. (iii) would question the validity of the technique used to reduce dimensionality. Therefore, we use three alternative DRTs: Principal Components Analysis (PCA), the three pass regression filter of Kelly and Pruitt (3PRF, 2015) and the Reduced Rank Regression (RRR) analysis, to test the robustness of our results. From a theoretical perspective, for the constructed factors to be valid proxies of the respective state variables, they should also satisfy equation (3.5), i.e. the market risk premium should also be an affine function of the proxies. The last two DRTs, as we explain below, deliver factors which by construction satisfy equation (3.5), whereas PCA does not necessarily do so. However, we still use PCA as a benchmark technique given its popularity in the literature of DRTs.

We follow Andreou et al. (2018) who substitute the unobservable variable X_t on the left-hand side of equation (3.9) into equation (3.5), to obtain

$$\mathrm{EP}(t,\tau) = \left(\beta_{ep,0}(\tau) - \beta_{ep}(\tau)^{\top}\bar{B}_n B_{n,0}\right) + \left(\beta_{ep}(\tau)^{\top}\bar{B}_n\right) M^{\mathbb{Q}}_{t,n} \tag{3.10}$$

that in absence of transaction costs 6 factors are sufficient to price the cross-section of equity returns.

Subsequently, we proxy for the EP in (3.10) with its realization, proxied by the return of the S&P 500 index, $r^e_{t,t+t}$, and obtain its fitted value using the 3PRF estimator of Kelly and Pruitt (2015). The estimate $\hat{r}^e_{t,t+t}$ has two properties: (i) it is an affine function of the term structure $M_{t,n}$ and hence can be regarded as a proxy of the state vector X_t, and (ii) it satisfies (3.5).

Finally, we follow Feunou et al. (2014) who instead of employing only a single horizon equity premium return, they employ the whole term structure of the equity premium. In particular, they stack the equity premiums of equation (3.5) across horizons $\tau = \tau_1, \tau_2, \ldots, \tau_q$ and substitute the state vector from equation (3.9) to obtain a system of linear restrictions of the following form

$$\mathrm{EP}_t = \Pi_0 + \Pi \, M^{\mathbb{Q}}_{t,n} \tag{3.11}$$

where EP_t is the $(q \times 1)$ vector of the q single-horizon equity premium returns, Π_0 is a $(q \times 1)$ vector and Π is $(q \times q)$ matrix of rank less or equal to q. For a given rank of matrix Π, $r \leq q$, equation (3.11) corresponds to a multivariate Reduced-Rank Regression (RRR). To this end, we employ the estimator provided by Hansen (2008). In Section 3.4, we discuss in detail the implementation of the three DRTs, in detail.

3.2.2 Estimation of Risk-Neutral Cumulants

We apply the Bakshi et al. (2003) formulae of risk-neutral moments (RNMs) to calculate the first three risk-neutral cumulants[6]

$$\begin{aligned}
M^{\mathbb{Q}}_{t,2}(\tau) &\equiv E^{\mathbb{Q}}_t(\tau)\left[\left(xr^e_{t,t+\tau} - E^{\mathbb{Q}}_t(\tau)\left[xr^e_{t,t+\tau}\right]\right)^2\right] \\
M^{\mathbb{Q}}_{t,3}(\tau) &\equiv E^{\mathbb{Q}}_t(\tau)\left[\left(xr^e_{t,t+\tau} - E^{\mathbb{Q}}_t(\tau)\left[xr^e_{t,t+\tau}\right]\right)^3\right] \\
M^{\mathbb{Q}}_{t,4}(\tau) &\equiv E^{\mathbb{Q}}_t(\tau)\left[\left(xr^e_{t,t+\tau} - E^{\mathbb{Q}}_t(\tau)\left[xr^e_{t,t+\tau}\right]\right)^4\right]
\end{aligned} \tag{3.12}$$

Let $H(S_{t+\tau})$ denote a twice differentiable payoff on the asset's price at time-$(t+\tau)$. The time-t arbitrage free price of H can be replicated by a position on the risk free asset, the stock, and a linear combination of out-of-the-money (OTM) call and put options as in

$$\begin{aligned}
E^{\mathbb{Q}}_t\left[e^{-r\tau}H(S)\right] = &\left(H(\bar{S}) - \bar{S}H_S(\bar{S})\right)e^{-r\tau} + H_S(\bar{S})S_t \\
&+ \int_{\bar{S}}^{\infty} H_{SS}(K)C(t,\tau;K)dK \\
&+ \int_0^{\bar{S}} H_{SS}(K)P(t,\tau;K)dK
\end{aligned} \tag{3.13}$$

where $\bar{S}$ is an arbitrary level of the stock at time-$(t+\tau)$, r is the continuously compounded risk-free rate at time-t with horizon $(t+\tau)$, H_S (H_{SS}) denotes the first (second) partial derivative of the payoff function.

The first three cumulants can be expressed in terms of the prices of the mean contract, $\mu_t(\tau) \equiv E^{\mathbb{Q}}_t[xr_{t,t+\tau}]$, the volatility contract, $V_t(\tau) \equiv E^{\mathbb{Q}}_t[e^{-r\tau}xr^2_{t,t+\tau}]$, the cubic contract, $W_t(\tau) \equiv E^{\mathbb{Q}}_t[e^{-r\tau}xr^3_{t,t+\tau}]$, and the quartic contract, $X_t(\tau) \equiv$

[6] The RNCs are non-standardised risk-neutral Moments. In particular, the risk-neutral volatility is the second RNC. risk-neutral Skewness is the third RNC standardised by the term $(E^{\mathbb{Q}}_t[xr_{t,t+\tau}] - E^{\mathbb{Q}}_t[xr_{t,t+\tau}]^2])^{3/2}$. Finally, risk-neutral Kurtosis is the fourth RNC standardised by the term $(E^{\mathbb{Q}}_t[xr_{t,t+\tau}] - E^{\mathbb{Q}}_t[xr_{t,t+\tau}]^2])^{4/2}$. Moreover, note that the Bakshi et al. (2003) formulae refer to actual and not excess returns. Since, though, the risk-free rate from t to $t+\tau$ is known at time-t, excess returns and returns have the same cumulants (as they are centralised moments).

$E_t^{\mathbb{Q}}[e^{-r\tau} r_{t,t+\tau}^4]$, respectively as in

$$M_{t,2}^{\mathbb{Q}}(\tau) = e^{r\tau} V_t(\tau) - \mu_t(\tau)^2 \tag{3.14}$$

$$M_{t,3}^{\mathbb{Q}}(\tau) = e^{r\tau} W_t(\tau) - 3\mu_t(\tau) e^{r\tau} V_t(\tau) + 2\mu_t(\tau)^3 \tag{3.15}$$

$$M_{t,4}^{\mathbb{Q}}(\tau) = e^{r\tau} X_t(\tau) - 4\mu_t(\tau) e^{r\tau} W_t(\tau) + 6\mu_t(\tau)^2 e^{r\tau} V_t(\tau) - 3\mu_t(\tau)^4 \tag{3.16}$$

where

$$\mu_t(\tau) \approx e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t,\tau) - \frac{e^{r\tau}}{6} W(t,\tau) - \frac{e^{r\tau}}{24} X(t,\tau) \tag{3.17}$$

Equation (3.13) yields the fair prices of the contracts as

$$\begin{aligned} V_t(\tau) = &\int_{S_t}^{\infty} \frac{2\left(1 - \ln\left[\frac{K}{S_t}\right]\right)}{K^2} C(t,\tau;K)dK + \\ &\int_0^{S_t} \frac{2\left(1 + \ln\left[\frac{S_t}{K}\right]\right)}{K^2} P(t,\tau;K)dK \end{aligned} \tag{3.18}$$

$$\begin{aligned} W_t(\tau) = &\int_{S_t}^{\infty} \frac{6\ln\left[\frac{K}{S_t}\right] - 3\left(\ln\left[\frac{K}{S_t}\right]\right)^2}{K^2} C(t,\tau;K)dK - \\ &\int_0^{S_t} \frac{6\ln\left[\frac{S_t}{K}\right] + 3\left(\ln\left[\frac{S_t}{K}\right]\right)^2}{K^2} P(t,\tau;K)dK \end{aligned} \tag{3.19}$$

and

$$\begin{aligned} X_t(\tau) = &\int_{S_t}^{\infty} \frac{12\left(\ln\left[\frac{K}{S_t}\right]\right)^2 - 4\left(\ln\left[\frac{K}{S_t}\right]\right)^3}{K^2} C(t,\tau;K)dK + \\ &\int_0^{S_t} \frac{12\left(\ln\left[\frac{S_t}{K}\right]\right)^2 + 4\left(\ln\left[\frac{S_t}{K}\right]\right)^3}{K^2} P(t,\tau;K)dK \end{aligned} \tag{3.20}$$

Equations (3.18) - (3.20), show that the arbitrage free prices of the contracts are computed as a weighted linear combination of out-of-the-money call and put options.

3.3 Data

We obtain daily S&P 500 European style index option data, the level of the S&P 500 index, the dividend yield of the S&P 500, and the continuously compounded risk-free rates from 1996 through 2017 from the Ivy DB database of OptionMetrics. We follow the existing literature, and we impose a number of filters on the option data set prior to extracting the RNCs. In particular, we discard options with zero open interest, with less than 5 days-to-maturity, whose best bid price is greater than the best offer price, and whose best bid price is less or equal to $3/8. We also discard duplicate prices per contract and day. We calculate the option price as the average of the best bid and best offer. Consequently, we eliminate in-the-money (ITM) options, as they are less liquid than OTM options. In line with Chang et al. (2013), we eliminate put (call) options whose strike prices are greater (less) than 103% (97%) of the underlying asset price, we discard option prices that violate Merton's (1973) arbitrage bounds and whose OM IvyDB implied volatility is not available.

The cross-sectional pricing exercises use daily and monthly stock return data obtained from the Center for Research in Securities Prices (CRSP) on all common stocks (share codes 10 and 11) traded in NYSE, NASDAQ, and Amex (exchange codes 1, 2, 3, 31, 32, and 33). The market return, the risk-free rate, the returns of the test assets, and the factor mimicking portfolio returns for size, book-to-market, and momentum factors are obtained from Ken French's website.

3.3.1 Estimation of Risk-Neutral Cumulants

For each one of the 5,517 trading days of our sample, spanning January 1996 to December 2017, we create single horizon RNCs for 30, 60, 91, 182, 273, and 365 days' horizons (corresponding roughly to 1, 2, 3, 6, 9, and 12 months). The calculation of the integrals in equations (3.18) to (3.20) require a continuum of out-of-the-money (OTM) calls and OTM put options whose expirations are constant across the trading dates. In contrast, the market provides a finite number of discrete strike prices whose maturities vary each day.

On each trading day, we create constant maturity RNCs as follows. For each contract, we first calculate its corresponding Black-Scholes-Merton implied volatility using a root finding algorithm. Subsequently, for the maturities with at least two available OTM call and put options, we create a fine grid for moneyness (K/S) levels ranging from 0.01% to 300% and interpolate in the implied volatility – moneyness space using a natural cubic spline. Beyond the moneyness levels of the available contracts, we extrapolate horizontally using the implied volatilities corresponding to the lowest and highest available strike prices. Once the grid is constructed, implied volatilities for moneyness levels less (greater) than 100% are translated back to put (call) option prices using Merton's (1973) formulas. Then, we calculate the integrals in equations (3.18) to (3.20) using trapezoidal numerical integration. To get the constant RNCs for the desired maturities we interpolate linearly accross the available maturities.

We estimate the RNCs with horizons greater than one month for all the 5,517 trading days in our sample. The one month horizon RNCs have not been estimated for 648 trading days. This is due to data availability. When there are no available contracts maturing after 5 days and in less than 31 days, the one month horizon RNCs are not computed.

3.3.2 Risk-neutral Cumulants: Descriptive Statistics

Table 3.1 reports the summary statistics for the levels of all maturities of the 2$^{\text{nd}}$ (Panel A), 3$^{\text{rd}}$ (Panel B), and 4$^{\text{th}}$ (Panel C) RNC term structure. As the order of a cumulant increases, the values of the cumulant drop by approximately a power of ten. For presentation purposes, prior to calculating the statistics of the 3$^{\text{rd}}$ and 4$^{\text{th}}$ RNC we have multiplied their corresponding time series by 10 and 100 respectively. The mean value of the 2$^{\text{nd}}$ RNC of returns increases monotonically from 0.004 to 0.058 as the returns' horizon increases from one to twelve months. Similarly, the mean value of the 3$^{\text{rd}}$ RNC (4$^{\text{th}}$ RNC) decreases (increases) monotonically from -0.005 (0.026) to -0.254 (3.199) across the horizons. Our findings are consistent with the previous literature that has studied the term structures of the risk-neutral moments or cumulants of the S&P 500 returns' distribution. This documents that under the risk-neutral measure, the distribution of the S&P 500 returns becomes more negatively skewed and exhibits heavier tails as the returns' horizon increases (see, among others, Neumann and Skiadopoulos, 2013; Feunou et al., 2014; Xie, 2014; Dotsis, 2017).

Column 'St.Dev'. reports the standard deviations of the time series. For all the RNCs, the standard deviations increase monotonically as the horizon increases. The less precise estimates of the longer horizons are likely due to the combination of the increased uncertainty which is inherent in longer horizons and the lower liquidity of the longer maturity contracts. Finally, column 'ADF' reports the statistic of the Augmented Dickey-Fuller test whose null hypothesis is that the time series contains a unit root. The test rejects the unit root hypothesis at the 5% statistical significance level for all the time series. Therefore, the series of RNCs are stationary and there is no need to difference them. Moreover, the last 6 columns of Table 3.1 report the pairwise correlations of the individual horizon time series within each term structure. The pairwise correlations of the time series comprising the term structure of the 2$^{\text{nd}}$ RNC range from 83% for the most distant horizons to 99% for the closest ones. Similarly, the pairwise correlations of the time series comprising the term structure of the 3$^{\text{rd}}$ (4$^{\text{th}}$) RNC range from 63% (59%) to 98% (95%). Overall, the high correlations suggest that each term structure exhibits a strong factor structure. Therefore, the informational content of each

RNC term structure may be summarised by a few factors.

3.4 Estimation of State Variables

In Section 3.2, we presented the setting of Feunou et al. (2014). Within their setting, the vector of the state variables, and thus the SDF, is an affine function of the term structure of the RNCs of the distribution of returns on aggregate consumption, which we proxy by the level of the $S\&P$ 500 index. A DRT applied to the term structure of a RNC yields factors that are a linear combination of the RNC's term structure. Hence, the derived factors may be regarded as proxies of the state variables. In this Section, we describe the three DRT methods we employ; namely the Principal Component Analysis (PCA), the reduced-rank regression analysis (RRR), and the three-pass regression filter (3PRF) of Kelly and Pruitt (2015). Then, we present the results on the constructed factors obained from each DRT method.

3.4.1 Principal Component Analysis

Our benchmark approach is PCA due to its popularity in the literature of DRTs. PCA is a statistical procedure that extracts uncorrelated factors from a set of variables, termed principal components (PCs). PCs are linear combinations of the variables and they are computed so that the first PC explains the largest possible variability of the variables, and each succeeding PC explains the largest possible variability left. For any given order RNC term structure, we apply the PCA to the scaled time series of the individual horizons. In line with common practice, we scale the time series to have zero mean and standard deviation equal to one.

Table 3.2 reports the loadings of the PCs extracted from the term structure of the 2^{nd} (Panel A), 3^{rd} (Panel B), and 4^{th} (Panel C) RNC. Moreover, in row 'R^2, entries report the percentage of the term structure's total variance explained by the n-th PC and in row 'Cum R^2' it reports the percentage explained by the first n PCs. All the term structures exhibit a strong factor structure. In particular, the first PC explains 95.2%, 88.5%, and 87.0% of the total variability of the term structure of the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC respectively. Moreover, the first two PCs explain 99.53%, 97.5%, and 96.9% of the total variability of the term structure of the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC respectively.

For the term structure of any given RNC, the first PC mimics the level of the term structure as it loads with roughly the same weight on the time series of each individual RNC maturity. The weights of the second (third) PC, suggest that it mimics the slope (curvature) of the term structure. Indeed, once we proxy the slope of a term structure as the difference between the 365 days horizon minus the 30 days horizon estimate, i.e. slope $= M^{\mathbb{Q}}_{t,n}(12m) - M^{\mathbb{Q}}_{t,n}(1m)$, we find that its correlation with the second PC (column PC2) equals 52%, 44%, and 42% for the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC, respectively. Similarly, the correlation between the curvature $= M^{\mathbb{Q}}_{t,n}(12m) - 2 \times M^{\mathbb{Q}}_{t,n}(6m) + M^{\mathbb{Q}}_{t,n}(1m)$ proxy of a term structure and PC3 equals 59%, 65%, and 62% for the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC, respectively.

3.4.2 Reduced Rank Regression Analysis

Equation (3.11) shows that the term structure of the equity premium is an affine function of the term structure of any given order RNC. In line with Feunou et al. (2014), we substitute the equity premium over a horizon τ with the realisation of the S&P 500 excess returns over the same horizon, $xr^e_{t,t+\tau}$. Moreover, we follow the common practice and scale all individual time series to have zero mean and standard deviation equal to one. This yields a system of linear equations of the following form

$$xr^e_{t+} = \Pi \, M^{\mathbb{Q}}_{t,n}, \tag{3.21}$$

where xr^e_{t+} is the term structure of the S&P 500 (log) excess returns, $M^{\mathbb{Q}}_{t,n}$ is the term structure of the n-th RNC, and Π is a matrix with rank less or equal to the number of horizons q. For a given hypothesis for the rank of matrix Π, equation (3.21) corresponds to a multivariate RRR. Furthermore, for a given rank condition, $\text{rank}(\hat{\Pi}) = r \leq q$, Hansen's (2008, see Theorem 5) formulae provide an estimator for Π such that the rank of the estimated matrix equals r, i.e. $\text{rank}(\hat{\Pi}) = r$.[7] Since, by construction, the rank of $\hat{\Pi}$ equals r, the q time series $(\hat{\Pi}M^{\mathbb{Q}}_{t,n})$ are linearly dependent. To extract the r linearly independent factors we must apply an orthogonalisation procedure such as the Gram-Schmidt procedure. Since, though, we are going to use the factors in a regression setting, we apply the PCA to $\hat{\Pi}M^{\mathbb{Q}}_{t,n}$, which provides a base yielding linearly independent *and* uncorrelated factors.

To estimate Π, we first need to choose an appropriate rank condition. In line with Feunou et al. (2014), we determine the rank of Π in two alternative ways, to asses robustness. First, we calculate the p values associated with the likelihood ratio test, by Anderson (1951), on the hypothesis: H_0 : $\text{rank}(\Pi) \leq r$ against $\text{rank}(\Pi) = q$. The rank of Π is determined as the minimum value of r such that the null hypothesis is not rejected at the 1% significance level. Second, for a given rank r, we regress the individual horizon time series of excess returns in xr^e_{t+} on the r estimated RRR factors. Subsequently, we compare the R^2s of the regressions for the different assumed values of the rank r. If the R^2s do not significantly increase by increasing the assumed rank r by one, then r factors from $M_{t,n}$ are sufficient to summarize its predictive content with respect to the term-structure xr^e_{t+} and thus the rank of Π should be equal to r.

Table 3.3 reports the results of the RRR analysis applied to the term structure of the 2[nd] (Panel A), 3[rd] (Panel B), and 4[th] (Panel C) RNC. In particular, column

[7]In linear models with more than one independent variables, called multivariate regressions, the RRR estimator takes into account the reduced rank restriction on the coefficient matrix Π. Without the rank condition, the RRR and the ordinary least squares (OLS) estimators would provide the same estimates.

'$r = 1$' reports in rows '1-month' to '12-months' the R^2s of the regressions of the 1-month to 12-months S&P 500 (log) excess returns on the variable that has been estimated for the hypothesis rank(Π) $= 1$ and row 'H_0 : rank(Π) $\leq r$' reports the p-value of the Anderson (1951) test. Similarly, columns ($r = 2$) to ($r = 6$) report the corresponding values for the hypotheses rank(Π) $= 2$ to rank(Π) $= 6$.

For any given order RNC term structure, the p value of Anderson's (1951) likelihood ratio test rejects the hypothesis that the rank(Π) ≤ 1 at the 1% significance level. In contrast, for the same level of statistical significance, the test does not reject the hypothesis rank(Π) ≤ 2 for any of the RNC term structures. Therefore, the first methodology suggests that the rank is equal to 2. In addition, the second methodology of selecting the rank, also suggests that the rank equals 2, as the inclusion of a third factor provides a significantly relatively lower increase in the R^2s compared to the inclusion of a second factor. For example, the inclusion of a second factor increases the R^2s of the predictive regressions on the 30-days horizon equity premium from 5.3 to 8.5 (60.4%), from 8.6 to 10.8 (26%), and from 6.6 to 7.9 (20%) for the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC respectively. The inclusion of a third factor provides comparatively marginal increases for the 2$^{\text{nd}}$ RNC (8.23%), 3$^{\text{rd}}$ (7.4%) and the 4$^{\text{th}}$ (12.7%) RNC. Overall, the evidence suggest that the rank of matrix Π equals 2. Therefore, the RRR analysis complements the PCA by showing that two factors are sufficient to explain the variability of each term structure by respecting at the same time the relation between the term structure of the market risk premium and that of a given order's RNC.

To provide an intuitive interpretation of the two RRR factors, we associate them to the first two PCs of each term-structure, which proxy its level and slope, respectively. The entries in row 'cor($\cdot, PC1$)' ('cor($\cdot, PC2$)') and columns '$r = 1$' and '$r = 2$' of Table 3.3, report the correlations between the first (second) PC and the first and second RRR factors, respectively. For example, the correlation between the first RRR factor extracted from the 2$^{\text{nd}}$ RNC term structure and the first (second) PC equals 45.3% (70.7%). The correlation of the second RRR factor extracted from the 2[nd] RNC term structure and the first (second) PC equals −6.8% (70.7%). Simillarly, the correlations between the RRR and the PCA factors extracted from the higher order RNC term structures show that the RRR fators mix the information contained in the first two PCs, but their effect on each term structure is hard to interpret. Overall, the correlations suggest that the RRR and the PCA factors contain similar information, which is *not* though, identical.

3.4.3 The three pass regression filter

Equation (3.10) shows that any τ horizon of the equity premium return is an affine function of the term structure of any given order RNC. We follow Andreou et al. (2018), and for any given order RNC, we construct one factor as the fitted value of the 30-day equity premium obtained from the following linear model

$$xr^e_{t,\,t+30\text{ days}} = \beta_0 + \beta^\top M^{\mathbb{Q}}_{t,\,n}, \tag{3.22}$$

where $xr^e_{t,t+30\text{ days}}$ is the realization of the S&P 500 excess return during the next 30-day period, β_0 is a scalar, and β is a $(q \times 1)$ vector. In line with Andreou et al. (2018), we estimate β_0 and β using the 3PRF estimator of Kelly and Pruitt (2015). In contrast to the PCA, the 3PRF DRT has the advantage that it constructs factors which explain most of the variability of the term structure of RNCs, and they also respect the relation between the market risk premium of a given horizon and the state variables as shown by (3.5) and (3.22). Therefore, the 3PRF factor may be a strict subset of the PCA factors which capture solely the variability of $M^{\mathbb{Q}}_{t,n}$. In line with Kelly and Pruitt (2015), we standardize the independent variables in $M^{\mathbb{Q}}_{t,n}$ to have unit time series variance.

We construct the 3PRF factor as follows. In the first pass, for each horizon τ_i, we run the time series regressions $M_{t,\,n}(\tau_i)^{\mathbb{Q}} = \phi_{0,i} + \phi_i xr^e_{t,\,t+30\text{ days}} + \epsilon_{i,t}$. Subsequently, we retain the estimated slopes $\hat{\phi}_i$ and in the second pass, for each time t_i, we run the cross sectional regressions $M^{\mathbb{Q}}_{t,n} = \phi_{0,t} + F_t\hat{\phi}_i$. The cross sectional regressions yield a time series of estimated slopes $\hat{F}_t$. Finally, in the third pass we estimate β_0 and β from the following regression $xr^e_{t,t+30\text{ days}} = \beta_0 + \beta\hat{F}_t + \eta_{t+\tau}$. The forecast $\hat{xr}^e_{t,t+30\text{ days}} = \hat{\beta}_0 + \hat{\beta}^\top M^{\mathbb{Q}}_{t,n}$ serves as our 3PRF factor.

To gauge the informational content of the 3PRF factor extracted from the term structure of a given order's RNC, we work as follows. First, we compare the predictive performance of the 3PRF and the RRR factors with respect to the S&P 500 excess return for horizons from one up to twelve months. Second, we compute the correlations of the 3PRF factor with the first two PCs that mimic the level and the slope of each term structure, respectively. For any given RNC term structure, the entries in column '3PRF' and rows '1-month' to '12-months' of Table 3.3, report the R^2s for the predictive regressions. The entry in row 'cor$(\cdot, PC1)$' ('cor$(\cdot, PC2)$') reports the correlation of the 3PRF factor with the first (second) PC.

For any given order's RNC term structure, the highest R^2s are achieved for the 30-days horizon. This is expected, as this was the target forecast variable. Interestingly, though, the 3PRF procedure outperforms the combined predictive power of the two RRR factors only for the 2$^{\text{nd}}$ RNC, where the R^2 equals 9.0% versus 6.9%. For the term structures of the higher order RNCs, the performance of the 3PRF factor is similar to the performance of the RRR factors combined. Finally, for any given RNC term structure, the informational content of the 3PRF factor is essentially identical to the second PC of the term structure, as the correlations are greater than 99.9% in absolute terms. The high correlations suggest that for any given order's RNC term structure we shouldn't expect the pricing performance of the second PC to differ from that of the 3PRF factor.

3.5 Are factors priced? Fama-MacBeth regressions

In the setting of Feunou et al. (2014), the state vector is a linear combination of the term structure of any given order RNC term structure of the returns' distribution of a claim on aggregate consumption. Hence, the affine transformations of the 2^{nd}, 3^{rd}, and 4^{th} RNC term structures, described in Section 3.4, may be regarded as factors that proxy the state vector. Furthermore, since the SDF is an affine function of the state variables (see equation (3.2)), they should price the cross-section of equity returns. To this end, we test the pricing performance of each factor, SV, by means of FM two-stage regressions. As a special case of using the whole term structure of RNCs, we also examine whether a single horizon RNC is priced. This corresponds to the linear combination, where the weights of the other maturities RNCs, but the employed one, are zero.

In the setting of Feunou et al. (2014), the SDF is a function of the excess return of a claim on aggregate consumption and the state variables. For this reason, we test the pricing performance of each SV, by the cross sectional regression

$$R_{i,t} - R_{f,t} = \lambda_0 + \lambda_{\text{MKT}} \left(R_{\text{MKT},t} - R_{f,t} \right) + \lambda_{SV} SV_t, \tag{3.23}$$

where $R_{i,t}$, $R_{\text{MKT},t}$, and $R_{f,t}$ are the monthly rates of return of the ith risky asset, the market portfolio, and the risk-free asset. λ_{MKT} and λ_{SV} are the prices of risk of the excess market return and the factor SV, respectively. The factor SV is said to be priced, if its estimated price of risk is significantly different to zero.

In line with Fama and MacBeth (1973), we estimate the prices of risk of the constructed factors and infer their statistical significance as follows. First, we choose a set of N test assets. For any given test asset, in the first stage, we estimate its betas by running a time series regression of T months of daily excess returns on the market's excess return and SV, as in

$$R_{i,t} - R_{f,t} = \beta_0 + \beta^i_{\mathrm{MKT}} \left(R_{\mathrm{MKT},t} - R_{f,t}\right) + \beta^i_{SV} SV_t + \epsilon_{i,t} \tag{3.24}$$

where β^i_{MKT} and β^i_{SV} are the measures of the ith risky asset's exposures to market excess return and the factor SV.[8] To obtain the prices of risk as percentages per month, prior to proceeding to the second step, we standardise the estimated betas to have zero mean and standard deviation equal to one. In the second stage, we run the cross-sectional regression of next month's excess returns on the estimated betas, as in

$$R_{i,t} - R_{f,t} = \lambda_0 + \lambda_{\mathrm{MKT}} \hat{\beta}^i_{\mathrm{MKT}} + \lambda_{SV} \hat{\beta}^i_{SV} + \eta_i \tag{3.25}$$

We repeat the procedure by rolling the beta estimation window forward by one month. At the end of the procedure, we have a time series of estimated λ's. Their average values yield the estimated prices of risk. To assess robustness, we perform the FM regressions for different sets of test assets and different beta estimation windows, separately. We consider the following test assets: (i) 25 portfolios formed on Size and Book-to-Market, (ii) 25 portfolios formed on operating profitability and investment, (iii) 49 industry portfolios, and (iv) 10 portfolios formed on momentum.

Table 3.4 reports the estimated prices of risk of the first two principal components (sub-columns PC1 and PC2) of the 2^{nd}, 3^{rd}, and 4^{th} RNC term structure, obtained via a beta estimation window equal to one (Panel A), three (Panel B), six (Panel C), and twelve months (Panel D). Entries in Panel E, report the prices of risk for the full sample FM regressions, where in the first stage, we estimate betas by running time series regressions on the full sample of daily returns and in the second stage we run the cross sectional regressions each month. The second stage,

[8]Note, that in principle, we could had augmented equation (3.24), by controlling for the other SVs we have constructed from any given DRT method. However, given that factors are orthogonal, the estimated SV betas in (3.24) will not change in the augmented version.

leads to a time series of estimated prices of risk. Their average value yields the full-sample estimated price of risk. The reported t-statistics in parenthesis, are calculated using Newey-West standard errors[9].

Overall, the results of the FM regressions presented in Table 3.4, suggest that the principal components of the term structures are not priced factors of risk, as the estimated prices of risk are either insignificant or not robustly significant when estimated using different beta estimation windows or across the different test assets. For example, the price of risk for the first PC of the 2$^{\text{nd}}$ RNC term structure, estimated using a one-month beta estimation window, equals -0.49% (t-stat$=-2.32$) for the 49 industry portfolios, and -0.61% (t-stat$=-2.80$) for the 10 portfolios formed on momentum. In contrast, the prices of risk estimated using the same test assets, are statistically indistinguishable from zero for longer beta estimation windows.

The entries in Table 3.5, report the prices of risk for the variables estimated via the reduced rank regression analysis (columns RRR1 and RRR2), the three pass regression filter (column 3PRF), and the single 1-, 3-, 6-, and 12-month horizon of the 2$^{\text{nd}}$ (Panel A), 3$^{\text{rd}}$ (Panel B) and 4$^{\text{th}}$ (Panel C) RNC, using a beta estimation window of three months. We present the results only for the three months beta estimation window, due to space constrains.[10]

The results of Table 3.5 suggest that the RRR factors, the 3PRF factor, and the individual horizons RNCs are not priced in the cross section of stock returns; the reported estimated prices of risk are either statistically indistinguishable from zero,

[9]Throughout the study, we compute t-statistics using NW standard errors, with the lag length (q) given by the automatic lag selection procedure of Newey and West (1994), where $q = \left[4(T/100)^{2/9}\right]$, and T is the sample size. For all the beta estimation windows, we estimate from 252 to 263 prices of risk, hence q is always equal to 5.

[10]The three month estimation window strikes a good balance between beta estimates that are not biased to outlier values, yet it is reasonably short to capture time variations in betas. The one-month beta estimation window may misestimate betas, as it uses between 15 and 23 daily return observations and thus one or two outlier observations are likely to have a large impact (see, e.g., Bali et al., 2017, chap. 8). Furthermore, longer than three months beta estimation periods are not reasonably short enough to allow the estimation of conditional time-varying betas.

or not robustly significant across the different test assets. Overall, the evidence is consistent with the results of Table 3.4 and indicates that variables extracted from the RNC term structures do not yield FM estimated prices of risk that are robustly significant different from zero.

3.6 Portfolio Sorts

The results in Section 3.5, indicate that the RNCs do not contain useful information to price equity returns. The insignificant results obtained via the FM regressions, though, are not conclusive for two reasons. (i) FM regressions assume a linear relationship between the risk assets' excess returns and their exposure to the risk factor, and they test whether the slope of the relationship is significantly different to zero. (ii) it is possible that the test assets we chose, even though diverse, do not contain sufficient dispersion in exposure to the risk factor. In this Section, we test whether a factor extracted from the term structure of a RNC, SV, is a priced factor of risk by means of portfolio sorts. As we discuss below, portfolio sorts address both of these issues.

To test whether a constructed factor SV is priced, we proceed as follows. First, we estimate the beta exposure of every common stock traded in NYSE, NASDAQ, and Amex on the market excess return and the factor SV, by running a time series regression of T months of the stock's daily excess returns on the market's excess return and SV, as in

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{\mathrm{MKT}}^i \left(R_{\mathrm{MKT},t} - R_{f,t}\right) + \beta_{\mathrm{SV}}^i SV_t + \epsilon_{i,t}, \tag{3.26}$$

where $R_{i,t}$, $R_{\mathrm{MKT},t}$, and $R_{f,t}$ are the daily rates of return of the ith risky asset, the market portfolio, and the risk-free asset. Then, at the end of the beta estimation period, we form P portfolios by ranking stocks on the basis of their β_{SV}^i exposure.

Hence, the constructed portfolios contain sufficient dispersion in exposure to the factor SV. Subsequently, we form value weighted portfolios. We weight each stock in the portfolio by its relative market value within the portfolio at the end of the beta estimation period and record the portfolio's return the subsequent month. Finally, we roll the beta estimation period by one month and repeat. To ensure robustness, we employ alternative sizes for the beta estimation window. At the end of the procedure, we have a time series of monthly portfolio returns. The average monthly cross sectional performance of the portfolios reveals the relationship between the return of a risky asset and its exposure to the risk factor.

The factor is priced if (i) the cross sectional pattern of the portfolios' returns is linear with respect to the factor beta, and (ii) the spread portfolio, that is long the portfolio containing the stocks with the highest betas and short the portfolio containing the stocks with the lowest betas, yields an average monthly return that is statistically different to zero. For each portfolio, we also estimate its Fama-French-Carhart four factor alpha, α_{FFC}, by regressing its monthly returns on the market, size, value, and momentum factors. This allows to check whether any significant alphas of the constructed portfolios may be a result of already known factors or the constructed factors are priced, indeed.

First, we study the monthly performance of decile stock portfolios constructed on the basis of their one-month beta estimates on either the first or the second PC of the 2$^{\text{nd}}$, 3$^{\text{rd}}$, and 4$^{\text{th}}$ RNC term structure. Entries in Table 3.6, report in columns '1' to '10' and '10 - 1', the average value of the pre-ranking estimated betas, the post ranking average returns, and the α_{FFC} of the respective decile and spread portfolios, constructed at the end of each month on the basis of their one month beta estimates on the first and second PC of the 2$^{\text{nd}}$ (Panels A and B, respectively), 3$^{\text{rd}}$ (Panels C and D, respectively) and 4$^{\text{th}}$ (Panels D and E, respectively) RNC term structure. t-statistics, calculated using Newey-West standard errors, are reported in parenthesis.

The pattern of the pre-ranking betas shows that the constructed portfolios have sufficient dispersion in exposure to the factor SV. For example, the average values of the pre-ranking betas for the 2$^{\text{nd}}$ RNC - PC1 formed portfolios, monotonically increase from -5.17 to 4.46, across the ten portfolios. Furthermore, the beta of the spread portfolio equals 9.63 with a t-statitic equal to 16.11. Hence, the difference between the exposure to the 2$^{\text{nd}}$ RNC - PC1 factor of the tenth and first portfolio is highly statistically significant. We can see that the average spread portfolio returns are insignificant for most of the cases. In the cases where significance is obtained, still the t-statistics are well below the threshold value of 3 (Harvey et al. (2016)), which should be used to avoid data mining concerns. Hence, the results indicate that the term structure of RNCs is not priced even in the case where portfolio sorts are employed as an alternative to the FM regressions. This conclusion is corroborated by the evidence that there is no monotonic relation between the average returns and alphas of the decile portfolios and their magnitude of exposure to any given factor.

Interestingly, though, we find that the stocks with the greatest positive (negative) exposure to the first PC of the 2$^{\text{nd}}$, (3$^{\text{rd}}$) and 4$^{\text{th}}$ RNC term structure, significantly underperform. For example, the average returns for the 2$^{\text{nd}}$ RNC - PC1 beta sorted Portfolios 1 to 9 seem to randomly range from 0.61% to 1.07% per month. On the contrary, Portfolio 10 produces a significantly lower return equal to -0.07% per month. The alpha of the portfolio is economically and statistically significant as it equals -1.06% per month or -12.0% per annum with a Newey-West adjusted t-statistic equal to -4.31. Similarly, Portfolio 1 (10) of the 3$^{\text{nd}}$ (4$^{\text{th}}$) RNC - PC1 beta sorted portfolios produces an alpha equal to -0.93% (-0.97%) per month or approximately -11% (-11%) per annum with a t-statistic equal to -4.23 (-4.04). The evidence overall suggests that even though the PCs are not priced in the cross-section of equities, yet they drive the risk-adjusted performance of stocks which are most positively (negatively) exposed to the 2$^{\text{nd}}$, (3$^{\text{rd}}$) and 4$^{\text{th}}$ RNC term structure.

To check whether results may be driven by the choice of the beta estimation window, we repeat the portfolio sorts exercise by estimating betas for longer estimation periods. Entries in Table 3.7, report the monthly post-ranking performance of Decile 1, 10, and the spread portfolios constructed on betas estimated using the past 3-, 6-, and 12-months daily returns. We can see that the principal components are not priced factors of risk, as the spread portfolio does not produce a significant alpha for any of the longer beta estimation periods. Moreover, Decile 10 (1) consisting of stocks sorted with respect to the first PC factor beta of the 2^{nd} and 4^{th} (3^{rd}) RNC term structure underperforms, yet the economical and statistical significance diminishes as the beta estimation period increases and becomes insignificant for the 12-month beta estimation period.

We repeat the asset pricing tests via portfolio sorts, in the case where stocks are sorted to portfolios based on their exposures with respect to the two RRR factors, the 3PRF factor, and the individual horizons of any given order's RNC term structure, separately. Entries in Table 3.8, report the monthly post ranking performance of Decile 1, 10, and spread portfolios constructed on the beta exposures of stocks, estimated using three months of daily returns,with respect to the two RRR factors (columns RRR1 and RRA2), the 3PRF factor (column 3PRF), and the single one, three, six, and twelve months horizons RNCs. Consistent with the results of the FM regressions, we can see that the variables are not priced in the cross section as the alphas of the spread portfolios are economically and statistically insignificant[11].

Finally, we repeat the asset pricing tests via portfolio sorts by sorting stocks in quintile rather than decile portfolios. Quintile sorts reduce the effect of any outliers to our tests. Table 3.9, report the performance of quintile stock portfolios. We sort stocks in portfolios using the rolling three month estimated beta with respect

[11] In Tables 3.7, 3.8, and 3.9, we present the results only for the three months beta estimation window, due to space constrains. The results for the other beta estimation windows yield qualitatively similar results and are available upon request.

to each one of the candidate state variables used in the previous analysis. We can see that the spread portfolios do not yield significant performance and hence none of the considered factors is priced.

3.7 Further Evidence

3.7.1 Evidence from an ICAPM setting

The factors we have employed in the analysis so far, are constructed from the levels of the term structure of RNCs and hence they are cast in levels themselves, too. This is because the Feunou et al. (2014) setting, motivates the construction of state variables in levels. An alternative setting under which the use of our constructed variables could also be motivated, is the ICAPM setting, where the innovations of the factors, rather than their levels, should be employed. Furthermore, the ICAPM setting is in line with the previous literature, that has studied the pricing performance of factors constructed from options written on the S&P 500 return distribution (Ang et al. (2006); Chang et al. (2013); Xie (2014); Dotsis (2017)). Hence, testing our factors in an ICAPM setting, will allow us to connect our findings to the previous literature. For any given factor, we proxy its innovations by the residuals of an autoregressive moving average (ARMA(1, 1)) model fitted to the time series of each SV. [12] Entries in Table 3.10, reports the FM estimated prices of risk, using a rolling window equal to one month, for the innovations of the first two PCs, the two RRR factors, the 3PRF factor, and the individual horizons of any given order's RNC term structure[13].

[12] In line with Chang et al. (2013), we use an ARMA(1, 1) to estimate the innovations of each factor. The results from our asset pricing tests, are robust when we proxy the innovations of any given factor by the first daily differences of its time series.

[13] In line with the literature, the asset pricing exercises in Section 3.7.1 use the daily returns within a month to estimate the beta exposure of test assets to each factor (see Ang et al., 2006; Chang et al., 2013; Xie, 2014; Dotsis, 2017, and references therein). The results for longer beta estimation windows equal to three, six, and twelve months, yield qualitatively similar results.

In our sample, the FM regressions indicate that the innovations of the considered variables are not priced in the cross section of stock returns, as the prices of risk are either statistically insignificant or not robust across the test assets. Ang et al. (2006) argue that to the extent that innovations in volatility predict subsequent deterioration of the investment opportunity set, the so-called leverage effect of Black (1976), stocks that perform well during periods of increasing volatility should earn lower expected returns as risk-averse investors are willing to pay a premium for such stocks (e.g., see, Campbell (1993, 1996)). We find that the 1-month horizon 2^{nd} RNC does not earn a negative risk-premium, as the prices of risk reported in Panel A - column 1M are either marginally statistically significant with a positive sign or statistically insignificant. The evidence is robust for longer beta estimation horizons (Panel A, columns 3M to 12M). Similarly, we find no evidence that the slope of the 2^{nd} RNC earns a negative sign as documented by Dotsis (2017).

We further explore the pricing performance of the innovations by means of portfolio sorts. Entries in Table 3.12, report the α_{FFC} of the lowest decile, highest decile, and spread portfolios constructed by ranking stocks on the basis of their one month beta estimate on the innovations of the state variables. Consistent with the FM regressions, we find that none of the variables are priced as the spread portfolios are economically and statistically insignificant.[14]

[14] A remark is in order at this point. We test whether the innovations of the slope of the 2^{nd} RNC are priced in the spirit of Feunou et al. (2014), Ang et al. (2006) and Chang et al. (2013). In particular, as the framework of Feunou et al. (2014) dictates, we extract the slope of the 2^{nd} RNC by applying the principal component analysis (PCA) on the levels of the 2^{nd} RNC. Furthermore, similarly to Ang et al. (2006) and Chang et al. (2013), we test whether the innovations of the slope are priced using relatively small beta estimation windows ranging from one to twelve months.

Dotsis (2017) employs a different approach. In particular, each month he uses the most recent 5-year 2^{nd} RNC term structure data and extracts the slope of the term structure by applying the PCA on the innovations rather than the levels of the 2^{nd} RNC. Subsequently, he estimates the beta exposure of each stock on the same 5-year window which is much larger than ours. Subsequently, he forms quintile portfolios and follows their return the subsequent month. The results of this exercise are presented in Table 4 of Dotsis (2017) and are rather weak in light of Harvey et al. (2016) criticism. First, there is no monotonic relationship between the beta exposure of the portfolios and their post-ranking returns. Second, both the return and the risk

3.7.2 RNS versus RNC: A revisit

Our previous findings suggest that the term structure and the individual horizons of the 3rd RNC are not priced in the cross section of equity returns. On the other hand, Chang et al. (2013) find that the innovations of the single one, two, and six month horizon RNS, earn a negative risk premium during the period ranging from January 1996 to December 2007. RNS is the 3rd cumulant normalised by the term $(E_t^{\mathbb{Q}}[r_{t,t+\tau}] - E_t^{\mathbb{Q}}[r_{t,t+\tau}]^2])^{3/2}$. Even though, both moments measure the asymmetry of the risk-neutral distribution, the normalising term alters significantly the time series of the 3rd RNC. We find, that the correlations between the one, three, six, and twelve months horizon 3rd RNC and RNS, equal -8%, -6%, -3%, and 12%, respectively.

Entries, in Table 3.12 report the pricing performance of stocks' exposure to both the levels (Panel A) and the innovations (Panel B) of RNS. Entries report, the α_{FFC} of the lowest decile, the highest decile and and spread portfolios constructed by ranking stocks on the basis of their beta exposure, estimated using one month, three months, and six months of daily returns, to the one month (column 1M), three month (column 3M), and six month (column 6M) horizon RNS.

We can see that the level of the RNS is not priced in the cross section of equity returns, as the performance of the spread portfolio is either marginally statistically significant or insignificant across the different maturities; the marginal significant results do not by pass Harvey's (2016) critical values. The results of Panel B show that in our extended sample the innovations of RNS are not priced either, as the a_{FFC} of the spread portfolio is statistically indistinguishable to zero across

adjusted return of the spread portfolio are marginally statistically significant with t-stats equal to -2.05 and -2.04, respectively.

all maturities. In sum, over our extended sample, the S&P 500 RNS is not priced, just as is the case with the 3rd RNC.[15]

3.8 Conclusions

We contribute to the literature which investigates whether index option prices contain information which can be used to construct factors of risk. We investigate whether factors that price the cross section of stock returns can be constructed from the the term structures of the 2nd, 3rd, and 4th risk neutral cumulant (RNC) of the S&P 500 returns distribution. Our research is motivated by the theoretical setting of Feunou et al. (2014). In their setting, the SDF and the equity premium are affine functions of the vector of the state variables. Furthermore, the state vector is an affine function of the term structure of any given order RNC. Hence, any linear combination of an RNC term structure may be considered as a proxy of the vector of the state variables, and thus as a factor of risk that prices the cross section of stock returns.

We construct factors that are an affine function of any given order's RNC term structure, by applying three alternative dimensionality reduction techniques (DRTs) to the term structure of any given order RNC, namely the principal components analysis, the three pass regression, and the reduction rank regressions. The last two methods yield factors which respect the fundamental relation between the market risk premium and state variables. Furthermore, we also employ, as factors

[15] The estimation procedure, described in Section 3.3.1, is very similar to the one followed by Chang et al. (2013, see Appendix A). In fact, we find that the correlation of our RNS estimate and the one of Chang et al. (2013), which is available to download at `http://jfe.rochester.edu/data.htm`, equals 96%. Furthermore, Chang et al. (2013) document that the portfolio that is long the stocks with the highest exposure to the innovations of RNS and short the stocks with the lowest exposure of RNS earns on average a monthly Fama-French-Carhart alpha equal to -0.80% (t-stat = -2.42) during the 1996-2007 period. We repeat their exercise and document an alpha equal to -0.61% (-0.64%) with a t-stat equal to -2.02 (-1.93) when we estimate the RNS innovations using an ARMA model (the daily differences). Hence, our results differ due to the different sample period and not due to the procedure we follow to estimate the innovations of RNS or to test their pricing performance.

of risk, the single horizon of any given order's RNC, which is a special case of the more general linear combination of RNCs with different maturities specification. We test the pricing performance of each factor, by a number of different specifications of FM regressions and portfolio sorts. Furthermore, to alleviate the potential concern that our results may be driven by the setting of Feunou et al. (2014), we also test the pricing performance of each constructed factor in an ICAPM setting.

We find that factors constructed from the RNC's of the S&P 500 return distribution are not priced in the cross section of equity returns. For any given order's RNC term structure, our result holds, regardless of whether we test (i) a factor constructed by a DRT or an individual horizon RNC, (ii) the pricing performance of any given factor by means of FM regressions or portfolio sorts, and (iii) if a factor is priced in the Feunou et al. (2014) or the ICAPM setting. Hence, our results echo the recent evidence, that most of the asset pricing anomalies documented by the previous literature do not hold, once more conservative critical values are used to assess significance, the effect of micro-cap stocks is downsized and more extended samples are used(see, e.g., Harvey et al., 2016; Hou et al., 2015). Our study takes all these three dimensions into account.

Table 3.1: Risk-Neutral Cumulants: Descriptive Statistics

Entries report descriptive statistics for the daily estimates of the Risk-Neutral Cumulants' term structure (1, 2, 3, 6, and 12 months) during the period January 1996 – December 2017. Prior to calculating the statistics for the 3rd (4th) Risk-Neutral Cumulants we multiply the time-series by 10 (100). The "ADF" column reports the statistic of the Augmented Dickey-Fuller test for the null hypothesis of a unit root of a univariate time series. The "Obs." Column reports the number of available observations in the sample. The last six columns report the pairwise correlation of the series. ***, and ** indicate statistical significance at the 1%, and 5% level, respectively.

Horizon	Mean	St.Dev.	25th pctl	median	75th pctl	ADF	Obs.	Pairwise Correlations					
Panel A: 2nd Risk Neutral Cumulant (Risk Neutral Variance)													
1	0.004	0.004	0.002	0.003	0.004	-5.77***	4869	1	0.99	0.97	0.92	0.87	0.83
2	0.008	0.008	0.004	0.006	0.010	-5.32***	5517		1	0.99	0.96	0.92	0.88
3	0.013	0.011	0.006	0.010	0.015	-5.17***	5517			1	0.98	0.95	0.92
6	0.028	0.020	0.015	0.023	0.033	-4.75***	5517				1	0.99	0.97
9	0.043	0.028	0.025	0.036	0.051	-4.37***	5517					1	0.98
12	0.058	0.037	0.035	0.050	0.070	-4.16***	5517						1
Panel B: 3rd Risk Neutral Cumulant [x10]													
1	-0.005	0.011	-0.005	-0.002	-0.001	-7.87***	4869	1	0.97	0.91	0.82	0.72	0.63
2	-0.015	0.028	-0.015	-0.008	-0.005	-6.58***	5517		1	0.98	0.91	0.83	0.73
3	-0.030	0.047	-0.032	-0.017	-0.010	-6.92***	5517			1	0.96	0.89	0.80
6	-0.089	0.107	-0.101	-0.057	-0.036	-6.27***	5517				1	0.96	0.89
9	-0.163	0.173	-0.187	-0.106	-0.070	-5.54***	5517					1	0.92
12	-0.254	0.256	-0.296	-0.172	-0.110	-5.26***	5517						1
Panel C: 4th Risk Neutral Cumulant [x100]													
1	0.026	0.095	0.003	0.007	0.018	-9.25***	4869	1	0.95	0.87	0.77	0.66	0.59
2	0.096	0.293	0.016	0.032	0.073	-7.06***	5517		1	0.96	0.89	0.81	0.72
3	0.213	0.534	0.042	0.085	0.186	-7.71***	5517			1	0.96	0.89	0.80
6	0.830	1.536	0.230	0.409	0.837	-7.10***	5517				1	0.96	0.88
9	1.761	2.747	0.559	0.902	1.813	-6.53***	5517					1	0.92
12	3.199	4.547	0.974	1.703	3.363	-5.86***	5517						1

Table 3.2: Estimation of State Variables: Principal Component Analysis

Entries report the loadings from the Principal Component Analysis (PCA) for the term-structure of each risk-neutral cumulant. Row R^2 reports the percentage of the term-structure's total variance explained by the nth principal component and row Cum R^2 reports the percentage explained by the first n principal components.

Horizon	PC1	PC2	PC3	PC4	PC5	PC6
Panel A: 2nd Risk Neutral Cumulant						
1	0.40	-0.58	0.40	-0.46	-0.24	0.28
2	0.41	-0.37	-0.00	0.21	0.33	-0.74
3	0.41	-0.18	-0.30	0.54	0.27	0.59
6	0.42	0.17	-0.42	0.08	-0.77	-0.17
9	0.41	0.39	-0.34	-0.63	0.42	0.04
12	0.40	0.57	0.68	0.24	0.00	0.01
R^2	95.20	4.33	0.30	0.11	0.05	0.02
Cum R^2	95.20	99.53	99.82	99.94	99.98	100
Panel B: 3rd Risk Neutral Cumulant [x10]						
1	0.39	-0.58	0.37	0.44	0.32	-0.28
2	0.42	-0.36	0.05	-0.11	-0.45	0.69
3	0.43	-0.16	-0.24	-0.55	-0.28	-0.59
6	0.43	0.15	-0.38	-0.22	0.73	0.28
9	0.41	0.39	-0.41	0.64	-0.30	-0.10
12	0.38	0.58	0.70	-0.16	-0.02	-0.02
R^2	88.53	8.99	1.51	0.51	0.33	0.13
Cum R^2	88.53	97.52	99.03	99.54	99.87	100
Panel C: 4th Risk Neutral Cumulant [x100]						
1	0.38	-0.61	0.42	-0.39	0.29	-0.28
2	0.42	-0.37	0.00	0.17	-0.48	0.65
3	0.43	-0.12	-0.36	0.53	-0.17	-0.60
6	0.43	0.17	-0.38	0.05	0.72	-0.34
9	0.41	0.39	-0.27	-0.68	-0.36	0.13
12	0.38	0.54	0.70	0.27	0.00	0.01
R^2	87.00	9.89	1.83	0.65	0.46	0.17
Cum R^2	87.00	96.89	98.73	99.37	99.83	100

Table 3.3: Estimation of State Variables: RRR and 3PRF

Entries report the explanatory power of the state variables that have been estimated via reduced rank regressions (RRR) and the three-way pass regression filter (3PRF) from the term-structures of the 2nd (Panel A), 3rd (Panel B), and 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution on the S&P 500 excess returns. We consider S&P 500 excess returns at horizons (τ) of 1, 2, 3, 6, 9, and 12 months. Each panel reports the R^2s associated with each of the individual equity return predictability regressions, $Y_{t+\tau} = \Pi X_t + \varepsilon_t$, for different hypothesis on the rank of the matrix Π (columns r = 1 to r = 6) and via the 3PRF (column 3PRF) procedure, where the forecast target variable is the 1-month S&P 500 excess returns and the explanatory variables are each term-structure. The last row reports the p-values associated with the likelihood ratio test of the rank of Π on the hypothesis $H_0\colon rank(\Pi) \leq r$ against $rank(\Pi) = 6$. Row $\mathrm{cor}(\cdot, PC1)$ ($\mathrm{cor}(\cdot, PC2)$) reports the correlation of the first (second) principal component with the two state variables that have been estimated via the RRR for $rank(\Pi) = 2$ (columns *r = 1* and *r = 2*) and the 3PRF procedure (column *3PRF*).

	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6	3PRF
Panel A: 2nd risk neutral cumulant (S&P 500 returns R^2s)							
1-month	5.3	8.5	9.2	9.2	9.3	9.51	9.0
2	9.6	9.8	10.3	10.4	10.6	10.6	4.1
3	9.5	9.6	9.9	10.0	10.0	10.2	3.7
6	11.35	12.1	12.4	12.4	12.4	12.4	4.2
9	7.06	8.1	8.7	8.7	8.7	8.7	3.3
12-months	3.73	5.0	5.6	5.7	5.7	5.7	2.3
$H_0\colon rank(\Pi) \leq r$	<0.01	0.11	0.42	0.61	0.85	0.60	
$\mathrm{cor}(\cdot, PC1)$	45.3%	-6.8%					-0.0%
$\mathrm{cor}(\cdot, PC2)$	70.7%	49.0%					>99.9%
Panel B: 3rd risk neutral cumulant (S&P 500 returns R^2s)							
1-month	8.6	10.8	11.6	12.6	12.7	12.9	8.6
2	11.8	11.9	12.8	14.0	14.2	14.2	6.6
3	10.8	11.3	11.9	12.1	12.2	12.4	6.3
6	14.0	14.0	14.0	14.1	14.1	14.1	6.7
9	10.3	10.5	10.7	10.8	10.8	10.8	4.5
12-months	7.3	7.7	8.3	8.4	8.5	8.5	2.9
$H_0\colon rank(\Pi) \leq r$	<0.01	0.02	0.33	0.75	0.98	0.94	
$\mathrm{cor}(\cdot, PC1)$	-64.3%	12.3%					0.7%
$\mathrm{cor}(\cdot, PC2)$	-64.7%	-40.0%					<-99.9%
Panel C: 4th risk neutral cumulant (S&P 500 returns R^2s)							
1-month	6.6	7.9	8.9	9.7	9.9	10.1	6.4
2	7.5	8.3	8.8	12.3	12.5	13.0	6.3
3	7.7	8.6	10.4	11.6	11.7	12.4	6.9
6	13.2	13.3	13.7	14.1	14.1	14.5	9.4
9	11.0	11.0	11.1	11.1	11.1	11.3	6.2
12-months	8.4	8.7	8.7	8.7	8.8	8.8	4.0
$H_0\colon rank(\Pi) \leq r$	<0.01	0.08	0.20	0.52	0.90	0.88	
$\mathrm{cor}(\cdot, PC1)$	55.9%	74.1%					0.60%
$\mathrm{cor}(\cdot, PC2)$	-75.0 %	38.3%					>99.9%

Table 3.4: Fama-MacBeth regressions: Levels of the estimated Principal Components

Entries report the prices of risk (percent per month) of the state variables estimated via full sample, and rolling-window two-pass Fama and MacBeth (1973) regressions. In the first stage, we estimate the test asset's betas by running a time series regression of one (Panel A), three (Panel B), six (Panel C), and twelve (Panel D) months of daily excess returns on $R_m - R_f$ and the state variable of interest. In the second stage, we run the cross-sectional regression of next month's excess return on the estimated betas. We repeat the procedure by rolling the beta estimation window by one month. For the full sample regressions (Panel E), in the first stage we estimate betas by running a time series regression of the full sample's daily returns, and in the second stage we run the cross-sectional regressions each month. Both procedures lead to a time series of estimated prices of risk. Entries report their average value and the *t*-statistic (in parenthesis) using Newey-West standard errors with 5 lags. ***, **, and * indicate statistical significance of the spread at the 1%, 5%, and 10% level, respectively.

	Price of risk (percent per month)					
	2nd RNC		3rd RNC		4th RNC	
Test assets	PC1	PC2	PC1	PC2	PC1	PC2
Panel A: One-month beta	(1)	(2)	(3)	(4)	(5)	(6)
25 Portfolios Formed on Size and Book-to-Market	-0.015	-0.025	0.326	0.282	-0.593	-0.786
	(-0.11)	(-0.19)	(1.03)	(0.52)	(-1.05)	(-0.71)
25 Portfolios Formed on Operating Profitability and Investment	-0.062	-0.009	0.234	0.349	-0.436	-0.788
	(-0.60)	(-0.085)	(0.95)	(1.08)	(-0.82)	(-1.05)
49 Industry Portfolios	-0.493**	0.186	2.358**	-0.856	-5.051*	0.748
	(-2.32)	(1.11)	(2.14)	(-1.48)	(-1.80)	(0.78)
10 Portfolios Formed on Momentum	-0.605***	-0.130	1.874***	1.370**	-3.467**	-2.878**
	(-2.80)	(-0.84)	(2.78)	(2.06)	(-2.18)	(-2.23)
Panel B: Three-month beta						
25 Portfolios Formed on Size and Book-to-Market	0.167	-0.093	-0.335	0.124	0.663	-0.294
	(1.06)	(-0.73)	(-0.75)	(0.41)	(0.81)	(-0.49)
25 Portfolios Formed on Operating Profitability and Investment	0.011	-0.005	-0.284	-0.083	0.686	0.158
	(0.11)	(-0.062)	(-0.62)	(-0.40)	(0.66)	(0.37)
49 Industry Portfolios	0.071	0.040	-0.233	0.157	1.053	-0.488
	(0.36)	(0.26)	(-0.37)	(0.31)	(0.74)	(-0.43)
10 Portfolios Formed on Momentum	-0.152	0.049	0.057	0.233	-0.001	-0.818
	(-0.87)	(0.38)	(0.13)	(0.64)	(-0.00)	(-0.87)

Table 3.4: (Continued)

Panel C: Six-month beta	(1)	(2)	(3)	(4)	(5)	(6)
25 Portfolios Formed on Size and Book-to-Market	0.061	-0.142	-0.103	0.236	0.269	-0.149
	(0.30)	(-1.00)	(-0.24)	(0.75)	-0.31	(-0.26)
25 Portfolios Formed on Operating Profitability and Investment	-0.122	0.129	0.061	-0.380*	0.066	0.582
	(-1.17)	(1.63)	(0.16)	(-1.89)	-0.08	(1.39)
49 Industry Portfolios	0.071	0.020	-0.170	-0.280	0.632	0.490
	(0.37)	(0.15)	(-0.32)	(-0.85)	-0.54	(0.65)
10 Portfolios Formed on Momentum	0.058	0.133	-0.135	0.378	0.739	-0.837
	(0.34)	(0.91)	(-0.27)	(1.43)	-0.71	(-1.61)
Panel D: Twelve-month beta						
25 Portfolios Formed on Size and Book-to-Market	-0.034	0.157	0.198	-0.251	-0.654	0.494
	(-0.26)	(1.04)	(0.62)	(-0.95)	(-0.99)	(1.04)
25 Portfolios Formed on Operating Profitability and Investment	-0.139*	0.139**	0.142	-0.398***	-0.173	0.699**
	(-1.67)	(2.07)	(0.55)	(-2.60)	(-0.35)	(2.06)
49 Industry Portfolios	-0.058	0.139	0.144	-0.297	-0.005	0.645
	(-0.35)	(1.28)	(0.35)	(-1.09)	(-0.01)	(1.13)
10 Portfolios Formed on Momentum	0.023	0.082	-0.532	0.198	1.040	-0.593
	(0.13)	(0.68)	(-1.32)	(0.67)	(1.23)	(-1.13)
Panel E: Full-sample betas						
25 Portfolios Formed on Size and Book-to-Market	-0.019	-0.037	0.042	0.023	-0.024	-0.024
	(-0.28)	(-0.39)	(0.54)	(0.30)	(-0.32)	(-0.38)
25 Portfolios Formed on Operating Profitability and Investment	0.047	-0.034	0.004	0.024	-0.006	-0.018
	(1.24)	(-0.72)	(0.078)	(0.48)	(-0.11)	(-0.35)
49 Industry Portfolios	0.008	-0.025	0.018	0.002	-0.026	0.015
	(0.082)	(-0.46)	(0.19)	(0.038)	(-0.29)	(0.25)
10 Portfolios Formed on Momentum	-0.113	0.070	0.100	0.055	-0.088	-0.114
	(-0.76)	(0.65)	(0.85)	(0.70)	(-0.93)	(-0.78)

Table 3.5: Fama-MacBeth regressions: Levels of state variables estimated using alternative methods

Entries report the prices of risk (percent per month) of the state variables extracted from Reduced-Rank Regressions described in Section 3.2 (columns RR1 and RR2), the Three-Pass Regression Filter procedure described in Section 3.3 (column 3PRF), and the single one-, three-, six-, and twelve-month horizon (columns 1, 2, 3, 6, and 12-month) of the 2nd (Panel A), 3rd (Panel C), and 4th (Panel D) Risk-Neutral Cumulant of the S&P 500 return distribution. Prices of risk are estimated via three month rolling-window two-pass Fama and MacBeth (1973) regressions. In the first stage, we estimate the test asset's betas by running a time series regression of three months of daily excess returns on $R_m - R_f$ and the state variable of interest. In the second stage, we run the cross-sectional regression of next month's excess return on the estimated betas. We repeat the procedure by rolling the beta estimation window by one month. The procedure leads to a time series of estimated prices of risk. Entries report their average value and the *t*-statistic (in parenthesis) using Newey-West standard errors with 5 lags. ***, **, and * indicate statistical significance of the spread at the 1%, 5%, and 10% level, respectively.

	Price of Risk (% per month)						
	RRR1	RRR2	3PRF	1-month	3-month	6-month	12-month
Panel A: 2nd Risk Neutral cumulant							
25 Size/BM	-0.210	0.215*	-0.094	0.167	0.151	0.141	0.067
	(-1.12)	(1.92)	(-0.74)	(1.12)	(0.96)	(0.81)	(0.36)
25 OP/Inv	-0.025	0.160	-0.003	0.004	-0.005	-0.022	0.049
	(-0.32)	(1.57)	(-0.036)	(0.044)	(-0.05)	(-0.20)	(0.40)
49 Ind	-0.171	0.434**	0.037	0.030	0.057	0.010	0.130
	(-1.14)	(2.24)	(0.24)	(0.16)	(0.28)	(0.049)	(0.69)
10 Mom	-0.020	0.298	0.057	-0.053	-0.114	-0.208	-0.172
	(-0.10)	(1.39)	(0.45)	(-0.35)	(-0.66)	(-1.17)	(-0.77)
Panel B: 3rd Risk Neutral cumulant							
25 Size/BM	-0.326	0.266	-0.182	-0.467	-0.320	-0.152	-0.133
	(-1.01)	(0.81)	(-0.58)	(-0.97)	(-0.85)	(-0.45)	(-0.46)
25 OP/Inv	-0.059	0.320*	0.071	-0.160	-0.173	-0.013	-0.223
	(-0.21)	(1.90)	(0.34)	(-0.41)	(-0.40)	(-0.031)	(-0.74)
49 Ind	-0.320	0.796**	-0.173	-0.324	-0.205	-0.065	-0.476
	(-0.76)	(2.22)	(-0.34)	(-0.34)	(-0.33)	(-0.11)	(-1.12)
10 Mom	-0.914**	-0.273	-0.237	-0.240	0.044	0.551	0.030
	(-2.22)	(-0.66)	(-0.63)	(-0.35)	(0.14)	(1.39)	(0.047)
Panel C: 4th Risk Neutral cumulant							
25 Size/BM	-0.790	-0.418	-0.349	0.952	0.491	0.258	0.117
	(-1.36)	(-0.90)	(-0.58)	(0.80)	(0.84)	(0.53)	(0.25)
25 OP/Inv	0.301	0.070	0.165	0.502	0.584	0.155	0.341
	(0.52)	(0.15)	(0.39)	(0.46)	(0.54)	(0.17)	(0.54)
49 Ind	0.084	-0.669	-0.416	2.289	1.043	0.657	1.093
	(0.15)	(-0.62)	(-0.38)	(0.72)	(0.70)	(0.53)	(1.40)
10 Mom	-1.211*	0.377	-0.810	1.745	0.276	-0.519	0.355
	(-1.92)	(0.53)	(-0.89)	(0.70)	(0.40)	(-0.58)	(0.30)

Table 3.6: Decile portfolio sorts on principal components: One-month beta estimation period

Entries report the monthly post-ranking performance of decile stock portfolios constructed at the end of each month, on the basis of their one-month beta estimates on the first and second principal components of the 2nd (Panel A and B), the 3rd (Panel C and D), and the 4th (Panel E and F) Risk-Neutral Cumulant of the S&P 500 return distribution. At the end of each rolling one-month period, we run the following regression on the daily returns of each stock

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{SV}^i SV_t + \varepsilon_{i,t},$$

where SV is the first or second principal component of the 2nd, 3rd, and 4th Risk-Neutral Cumulant's term-structure. We sort stocks in ascending order with respect to their β_{SV}^i estimate and assign them to ten equally populated portfolios. We form value-weighted portfolios by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) within the portfolio at the end of the beta estimation period. For each portfolio, we record its value-weighted average beta (pre-ranking betas) and its value-weighted subsequent monthly return (post-ranking returns). For each portfolio, the table reports (columns 1 to 10) the average value of the time-series of its pre-ranking betas, of its post-ranking value-weighted monthly returns (in percent), and its Fama-French-Carhart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD. The final column (10 – 1) presents the results for the spread portfolio between the portfolios of stocks with the highest and lowest estimated betas. *t*-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Decile Portfolio										
	1	2	3	4	5	6	7	8	9	10	10 – 1
Panel A: 2nd Risk Neutral Cumulant – 1st Principal Component											
PC1 Beta	-5.17***	-2.53***	-1.49***	-0.82***	-0.30***	0.15***	0.63***	1.24***	2.17***	4.46***	9.63***
	(-16.00)	(-15.81)	(-15.66)	(-15.14)	(-11.52)	(7.83)	(15.8)	(16.24)	(16.06)	(15.70)	(16.11)
Average Return	0.81*	1.08**	1.07***	0.86**	0.91***	0.71**	0.70**	0.61*	0.91**	-0.07	-0.88**
	(1.72)	(2.71)	(3.25)	(2.87)	(3.31)	(2.72)	(2.36)	(1.78)	(2.39)	(-0.12)	(-2.83)
Carchart 4-factor alpha	-0.17	0.18	0.28*	0.05	0.15**	-0.03	-0.07	-0.25**	0.03	-1.06***	-0.89**
	(-0.76)	(1.14)	(1.84)	(0.54)	(2.17)	(-0.47)	(-0.80)	(-2.23)	(0.20)	(-4.31)	(-2.70)
Panel B: 2nd Risk Neutral Cumulant - 2nd Principal Component											
PC2 Beta	-14.35***	-7.06***	-4.03***	-2.09***	-0.53***	0.93***	2.56***	4.68***	7.96***	16.22***	30.58***
	(-18.02)	(-17.65)	(-17.23)	(-15.97)	(-8.08)	(12.26)	(16.4)	(17.1)	(17.2)	(17.76)	(18.3)
Average Return	0.44	0.49	0.51	0.86**	0.90***	1.03***	0.98***	0.88***	0.89**	0.73	0.29
	(0.82)	(1.17)	(1.46)	(2.85)	(3.39)	(3.84)	(3.52)	(3.00)	(2.32)	(1.31)	(0.82)
Carchart 4-factor alpha	-0.53**	-0.42**	-0.34***	0.07	0.13	0.24**	0.18*	0.07	0.01	-0.27	0.26
	(-2.22)	(-2.32)	(-3.3)	(0.67)	(1.62)	(2.52)	(1.75)	(0.55)	(0.04)	(-1.05)	(0.73)

Table 3.6: (Continued)

Panel C: 3rd Risk Neutral Cumulant - 1st Principal Component											
PC1 Beta	-11.92***	-5.82***	-3.32***	-1.73***	-0.46***	0.71***	2.02***	3.72***	6.4***	13.04***	24.96***
	(-9.05)	(-9.01)	(-8.96)	(-8.76)	(-6.86)	(8.60)	(9.21)	(9.19)	(9.17)	(9.36)	(9.26)
Average Return	0.01	0.65*	0.56	0.73**	0.76**	0.92***	0.96***	1.06***	1.03**	0.81*	0.80**
	(0.02)	(1.74)	(1.62)	(2.52)	(2.65)	(3.47)	(3.33)	(3.07)	(2.83)	(1.66)	(2.60)
Carchart 4-factor alpha	-0.93***	-0.23	-0.27**	-0.06	-0.04	0.17**	0.16*	0.24*	0.15	-0.18	0.75**
	(-4.23)	(-1.61)	(-2.43)	(-0.67)	(-0.39)	(2.14)	(1.79)	(1.78)	(1.11)	(-0.90)	(2.65)
Panel D: 3rd Risk Neutral Cumulant - 2nd Principal Component											
PC2 Beta	-28.71***	-14.06***	-8.18***	-4.41***	-1.37***	1.29***	4.25***	8.01***	13.75***	28.14***	56.85***
	(-9.15)	(-9.09)	(-9.16)	(-9.03)	(-7.83)	(6.85)	(8.68)	(9.04)	(9.19)	(9.41)	(9.33)
Average Return	0.65	0.70*	1.03***	0.87***	0.84***	0.86***	1.00***	0.64*	0.55	0.51	-0.13
	(1.18)	(1.82)	(3.53)	(3.23)	(3.31)	(3.04)	(3.57)	(1.86)	(1.28)	(0.93)	(-0.33)
Carchart 4-factor alpha	-0.3	-0.17	0.22**	0.08	0.06	0.07	0.2**	-0.21	-0.35**	-0.47	-0.17
	(-1.19)	(-1.09)	(2.17)	(0.74)	(0.62)	(0.98)	(1.97)	(-1.55)	(-1.98)	(-1.65)	(-0.43)
Panel E: 4th Risk Neutral Cumulant - 1st Principal Component											
PC1 Beta	-26.29***	-12.97***	-7.52***	-4.09***	-1.44***	0.94***	3.54***	6.78***	11.84***	24.27***	50.56***
	(-7.32)	(-7.22)	(-7.28)	(-7.22)	(-6.84)	(5.86)	(6.92)	(7.11)	(7.16)	(7.13)	(7.26)
Average Return	0.85*	0.95**	1.08***	1.01***	0.9***	0.71**	0.69**	0.64*	0.61	-0.01	-0.87**
	-1.7	(2.73)	(3.18)	(3.57)	(3.22)	(2.44)	(2.30)	(1.90)	(1.56)	(-0.03)	(-2.77)
Carchart 4-factor alpha	-0.12	0.12	0.23*	0.2**	0.15*	-0.05	-0.11	-0.21**	-0.3**	-0.97***	-0.85**
	(-0.56)	(0.89)	(1.88)	(2.11)	(1.68)	(-0.65)	(-1.29)	(-1.98)	(-2.15)	(-4.04)	(-2.81)
Panel F: 4th Risk Neutral Cumulant - 2nd Principal Component											
PC2 Beta	-53.64***	-26.06***	-15.08***	-8.06***	-2.52***	2.54***	8.09***	15.16***	26.22***	53.45***	107.09***
	(-7.28)	(-7.13)	(-7.11)	(-6.87)	(-5.65)	(6.38)	(7.27)	(7.26)	(7.19)	(7.24)	(7.29)
Average Return	0.58	0.38	0.78**	0.95***	0.76**	0.89***	0.98***	0.94***	0.7*	0.68	0.09
	(1.1)	(0.89)	(2.49)	(3.4)	(2.63)	(3.54)	(3.38)	(3.24)	(1.94)	(1.24)	(0.24)
Carchart 4-factor alpha	-0.44*	-0.52***	-0.06	0.11	-0.02	0.13	0.23**	0.12	-0.15	-0.23	0.21
	(-1.7)	(-2.97)	(-0.67)	(1.2)	(-0.17)	(1.41)	(2.22)	(1.34)	(-1.18)	(-0.93)	(0.55)

Table 3.7: Decile portfolio sorts on principal components: Longer beta estimation periods

Entries report the monthly post-ranking performance of the lowest decile (column 1), the highest decile (column 10), and the spread (column 10 – 1) stock portfolios constructed on the basis of the stocks' beta exposure on the first (columns PC1) and second (columns PC2) principal components of the 2nd (Panel A), the 3rd (Panel B), and the 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution. At the end of each rolling month period, we run the following regression on the daily returns of each stock during the past 3, 6, and 12-months

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{SV}^i SV_t + \varepsilon_{i,t},$$

where SV is the first or second principal component of the 2nd, 3rd, and 4th Risk-Neutral Cumulant's term-structure. We sort stocks in ascending order with respect to their β_{SV}^i estimate and assign them to ten equally populated portfolios. We form value-weighted portfolios by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) within the portfolio at the end of the beta estimation period. For each portfolio, we record its value-weighted average beta (pre-ranking betas) and its value-weighted subsequent monthly return (post-ranking returns). The table reports the Fama-French-Carchart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD for the portfolio containing the stocks with the lowest (highest) β_{SV}^i in subcolumn 1 (10) and the spread portfolio in subcolumn 10 – 1. t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and significant at the 1% level, but for readability reasons the stars are omitted.

	PC1			PC2		
	1	10	10 – 1	1	10	10 – 1
Panel A: 2nd Risk-Neutral Cumulant						
3-month Beta	-1.86	1.41	3.27	-4.63	6.04	10.67
Carchart 4-factor alpha	-0.28	-0.67**	-0.38	-0.20	-0.31	-0.11
	(-0.83)	(-2.94)	(-0.81)	(-0.99)	(-1.21)	(-0.31)
6-month Beta	-0.99	0.68	1.67	-2.38	3.44	5.82
Carchart 4-factor alpha	-0.11	-0.38*	-0.27	-0.64***	-0.08	0.56
	(-0.37)	(-1.89)	(-0.65)	(-3.09)	(-0.37)	(1.53)
12-month Beta	-0.51	0.34	0.85	-1.30	1.95	3.25
Carchart 4-factor alpha	-0.10	-0.40	-0.30	-0.64**	0.23	0.87*
	(-0.35)	(-1.56)	(-0.70)	(-2.47)	(0.80)	(1.81)
Panel B: 3rd Risk-Neutral Cumulant						
3-month Beta	-3.61	4.31	7.92	-9.42	8.55	17.96
Carchart 4-factor alpha	-0.71***	-0.22	0.48	-0.38	-0.32	0.06
	(-3.00)	(-0.70)	(1.09)	(-1.51)	(-1.45)	(0.18)
6-month Beta	-1.71	2.17	3.88	-4.89	4.21	9.10
Carchart 4-factor alpha	-0.51**	-0.24	0.27	0.04	-0.27	-0.32
	(-2.66)	(-0.84)	(0.72)	(0.20)	(-1.43)	(-0.96)
12-month Beta	-0.83	1.13	1.96	-2.39	2.02	4.41
Carchart 4-factor alpha	-0.29	-0.31	-0.02	1.44**	0.58	-0.86*
	(-1.01)	(-0.99)	(-0.04)	(2.41)	(1.22)	(-1.82)
Panel C: 4th Risk-Neutral Cumulant						
3-month Beta	-8.68	7.18	15.85	-15.65	16.56	32.21
Carchart 4-factor alpha	-0.10	-0.81***	-0.71	-0.34*	-0.42	-0.07
	(-0.30)	(-3.13)	(-1.47)	(-1.69)	(-1.62)	(-0.21)
6-month Beta	-4.31	3.30	7.62	-7.73	8.36	16.09
Carchart 4-factor alpha	-0.06	-0.42**	-0.36	-0.35*	0.18	0.54*
	(-0.18)	(-2.07)	(-0.88)	(-1.88)	(0.89)	(1.69)
12-month Beta	-2.14	1.55	3.69	-3.59	3.91	7.49
	(-5.7)	(6.04)	(5.97)	(-6.06)	(5.85)	(6.09)
Carchart 4-factor alpha	-0.01	-0.47	-0.46	-0.54**	0.51*	1.04**
	(-0.04)	(-1.62)	(-0.97)	(-2.15)	(1.86)	(2.33)

Table 3.8: Decile portfolio sorts on RRR, 3PRF, and single maturity factors

Entries report the monthly post-ranking performance of decile stock portfolios constructed on the basis of their three-month beta estimates on state variables estimated via Reduced-Rank Regressions described in Section 3.2 (columns RR1 and RR2), the Three-Pass Regression Filter procedure described in Section 3.3 (column 3PRF), or the single one-, three-, six-, and twelve-month horizon (columns 1, 2, 3, 6, and 12-month) of the 2nd (Panel A), the 3rd (Panel B), and the 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution, separately. At the end of each rolling three-month period, we run the following regression on the daily returns of each stock

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i \left(R_{m,t} - R_{f,t}\right) + \beta_{SV}^i SV_t + \varepsilon_{i,t},$$

where SV is one of the state variables described above. We then sort stocks in ascending order with respect to their β_{SV}^i estimate and assign them to ten equally populated portfolios. We form value-weighted portfolios by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) in the portfolio at the end of the beta estimation period. For each portfolio, we record its value-weighted subsequent monthly return (post-ranking returns). The table reports the Fama-French-Carhart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD for the portfolio containing the stocks with the lowest (highest) β_{SV}^i in row Decile-1 (Decile-10) and the spread portfolio in row Spread (10 – 1). *t*-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

	RR1	RR2	3PRF	1-month	3-month	6-month	12-month
Panel A: 2nd Risk-Neutral Cumulant							
Decile - 1 α_{FFC}	-0.19	-0.33	-0.20	-0.14	-0.40	-0.22	-0.16
	(-0.63)	(-1.28)	-1.03	(-0.48)	(-1.14)	(-0.61)	(-0.50)
Decile - 10 α_{FFC}	-0.38	-0.02	-0.25	-0.53**	-0.73***	-0.69**	-0.67**
	-1.58	-0.08	-1.00	(-2.72)	(-3.09)	(-2.71)	(-2.66)
Spread (10 – 1) α_{FFC}	-0.19	0.31	-0.05	-0.39	-0.33	-0.47	-0.52
	(-0.47)	(0.76)	-0.15	(-0.98)	(-0.68)	(-0.91)	(-1.05)
Panel B: 3rd Risk-Neutral Cumulant							
Decile - 1 α_{FFC}	-0.09	-0.53**	-0.27	-0.67***	-0.70***	-0.77***	-0.45*
	(-0.37)	(-2.45)	(-1.19)	(-3.61)	(-3.05)	(-3.16)	(1.89)
Decile - 10 α_{FFC}	-0.64**	-0.12	-0.37	-0.10	-0.15	-0.13	-0.07
	(-2.89)	(-0.42)	(-1.51)	(-0.36)	(-0.52)	(-0.36)	(-0.22)
Spread (10 – 1) α_{FFC}	-0.55	0.41	-0.10	0.57	0.55	0.64	0.38
	(-1.53)	(1.15)	(-0.30)	(1.52)	(1.27)	(1.25)	(0.89)
Panel C: 4th Risk-Neutral Cumulant							
Decile - 1 α_{FFC}	-0.35	-0.83***	-0.33	-0.14	-0.12	-0.15	-0.01
	(-1.26)	(-3.74)	(-1.61)	(-0.43)	-0.35	(-0.42)	(-0.01)
Decile - 10 α_{FFC}	-0.23	-0.33	-0.43*	-0.63***	-0.75***	-0.76**	-0.55**
	(-1.02)	(-1.20)	(-1.70)	(-3.13)	(-3.03)	(-2.79)	(-2.27)
Spread (10 – 1) α_{FFC}	0.12	0.50	-0.10	-0.49	-0.63	-0.60	-0.54
	(0.29)	(1.37)	(-0.27)	(-1.09)	(-1.27)	(-1.14)	(-1.17)

Table 3.9: Quintile portfolio sorts on each variable: Three-month beta estimation window

Entries report the monthly post-ranking performance of quintile stock portfolios constructed on the basis of their three-month beta estimates on state variables estimated via the Principal Component Analysis (columns PC1 and PC2), Reduced-Rank Regressions described in Section 3.2 (columns RR1 and RR2), the Three-Pass Regression Filter procedure described in Section 3.3 (column 3PRF), or the single one-, three-, six-, and twelve-month horizon (columns 1, 2, 3, 6, and 12-month) of the 2nd (Panel A), the 3rd (Panel B), and the 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution. At the end of each rolling three-month period, we run the following regression on the daily returns of each stock

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i \left(R_{m,t} - R_{f,t}\right) + \beta_{SV}^i SV_t + \varepsilon_{i,t},$$

where SV is one of the state variables described above. We then sort stocks in ascending order with respect to their β_{SV}^i estimate and assign them to five equally populated portfolios. We form value-weighted portfolio by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) in the portfolio at the end of the beta estimation period. For each portfolio, we record its value-weighted subsequent monthly return (post-ranking returns). Entries report the Fama-French-Carhart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD for the portfolio containing the stocks with the lowest (highest) β_{SV}^i in row Quintile-1 (Quintile-5) and the spread portfolio in row Spread. *t*-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

	Fama-French-Carchart 4-factor alpha (α_{FFC})								
	PC1	PC2	RR1	RR2	3PRF	1-month	3-month	6-month	12-month
Panel A: 2nd Risk-Neutral Cumulant									
Quint-1	-0.06	-0.25	-0.17	-0.15	-0.23*	-0.13	-0.01	-0.02	-0.02
	(-0.27)	(-1.81)	(-0.85)	(-0.89)	(-1.68)	-0.65	(-0.03)	(-0.11)	-0.12
Quint.-5	-0.35**	-0.11	-0.19	0.00	-0.15	-0.30**	-0.38***	-0.42***	-0.29*
	(-2.48)	(-0.68)	(-1.03)	(0.01)	(-0.90)	(-2.49)	(-2.67)	(-2.79)	(-1.80)
5 – 1	-0.29	0.14	-0.03	0.15	0.08	-0.16	-0.38	-0.39	-0.27
	(-1.03)	(0.64)	(-0.08)	(0.52)	(0.38)	(-0.62)	(-1.34)	(-1.33)	(-0.92)
Panel B: 3rd Risk Neutral cumulant									
Quint.-1	-0.41**	-0.23	-0.09	-0.42***	-0.24	-0.34**	-0.51***	-0.37**	-0.29**
	(-2.47)	(-1.45)	(-0.50)	(-2.79)	(-1.60)	(-2.56)	(-3.16)	(-2.43)	(-1.96)
Quint.-5	-0.12	-0.25	-0.49***	0.02	-0.24	-0.19	-0.08	-0.16	0.01
	(-0.58)	(-1.64)	(-3.33)	(0.10)	(-1.47)	(-1.01)	(-0.43)	(-0.64)	(0.06)
5 – 1	0.29	-0.02	-0.40	0.43	0.00	0.15	0.43	0.21	0.30
	(0.97)	(-0.06)	(-1.47)	(1.74)	0.00	(0.56)	(1.58)	(0.58)	(0.96)
Panel B: 4th Risk Neutral cumulant									
Quint.-1	-0.10	-0.18	-0.24	-0.53	-0.20	-0.12	0.00	0.09	0.02
	(-0.48)	(-1.21)	(-1.46)	(-3.20)	(-1.37)	(-0.58)	(0.02)	(0.44)	(0.09)
Quint.-5	-0.40**	-0.23	-0.18	-0.04	-0.21	-0.43***	-0.58***	-0.43***	-0.33**
	(-2.25)	(-1.58)	(-1.10)	(-0.21)	(-1.39)	(-3.04)	(-3.51)	(-3.08)	(-2.17)
5 – 1	-0.29	-0.05	0.06	0.49*	-0.01	-0.30	-0.58**	-0.51*	-0.35
	(-0.87)	(-0.21)	-0.22	(-1.79)	(-0.05)	(-0.99)	(-2.01)	(-1.85)	(-1.09)

Table 3.10: Fama-MacBeth regressions: Innovations of the state variables

Entries report the prices of risk (percent per month) of innovations of the state variables estimated via Principal Component Analysis (columns PC1 and PC2) Reduced-Rank Regressions described in Section 3.2 (columns RR1 and RR2), the Three-Pass Regression Filter procedure described in Section 3.3 (column 3PRF), or the single one-, three-, six-, and twelve-month horizon (columns 1, 2, 3, 6, and 12-month) of the 2nd (Panel A), the 3rd (Panel B), and the 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution, separately. Prices of risk are estimated via rolling-window two-pass Fama and MacBeth (1973) regressions. In the first stage, we estimate the test asset's betas by running a time series regression of daily excess returns on $R_m - R_f$ and the state variable of interest during the month. In the second stage, we run the cross-sectional regression of next month's excess return on the estimated betas. We repeat the procedure by rolling the beta estimation window by one month. The procedure leads to a time series of estimated prices of risk. The table reports their average value and the t-statistic (in parenthesis) using Newey-West standard errors with 5 lags. ***, and ** indicate statistical significance of the spread at the 1%, and 5% level, respectively.

	Price of Risk (% per month)								
	PC1	PC2	RRR1	RRR2	3PRF	1M	3M	6M	12M
Panel A: 2nd Risk-Neutral Cumulant									
25 Size/BM	0.181	-0.059	-0.085	-0.191	-0.059	0.177	0.081	0.159	0.165
	(1.39)	(-0.49)	(-0.69)	(-1.34)	(-0.49)	(1.53)	(0.56)	(1.27)	(1.35)
25 OP/Inv	0.163	-0.103	0.088	0.013	-0.107	0.181*	0.112	0.093	0.148
	(1.37)	(-1.21)	(1.16)	(0.096)	(-1.27)	(1.71)	(1.07)	(0.78)	(1.05)
49 Ind	-0.062	-0.170	-0.181	0.315	-0.184	0.033	-0.059	-0.163	0.025
	(-0.27)	(-1.06)	(-1.06)	(1.35)	(-1.15)	(0.18)	(-0.29)	(-0.68)	(0.11)
10 Mom	0.157	0.012	0.085	0.224	-0.001	0.022	0.096	0.063	0.189
	(0.87)	(0.08)	(0.48)	(0.89)	(-0.01)	(0.15)	(0.47)	(0.37)	(0.77)
Panel B: 3rd Risk Neutral cumulant									
25 Size/BM	-0.331	0.324	0.368	0.104	-0.321	-0.804*	-0.072	-0.398	-0.035
	(-1.06)	(1.12)	(1.18)	(0.26)	(-1.10)	(-1.90)	(-0.20)	(-1.20)	(-0.14)
25 OP/Inv	-0.419	0.393	0.044	0.252	-0.401	-0.626	-0.256	-0.064	-0.235
	(-1.48)	(1.45)	(0.20)	(0.99)	(-1.49)	(-1.56)	(-1.07)	(-0.26)	(-0.81)
49 Ind	0.274	0.740	-0.938	0.337	-0.747	-0.404	0.705	0.807	0.282
	(0.67)	(1.51)	(-1.41)	(0.56)	(-1.55)	(-0.86)	(1.12)	(1.39)	(0.61)
10 Mom	-0.022	0.135	-0.727	-1.138*	-0.157	-0.855	-0.446	0.075	0.066
	(-0.041)	(0.30)	(-1.36)	(-1.91)	(-0.34)	(-1.16)	(-0.68)	(0.24)	(0.12)
Panel B: 4th Risk Neutral cumulant									
25 Size/BM	0.917	-0.836	0.282	0.518	-0.761	2.010*	0.348	0.444	-0.250
	(1.18)	(-1.49)	(0.71)	(1.26)	(-1.40)	(1.78)	(0.50)	(0.60)	(-0.45)
25 OP/Inv	0.976	-1.018	0.782	0.733	-0.927	1.773	0.221	1.063	0.716
	(1.39)	(-1.21)	(1.29)	(0.95)	(-1.20)	(1.17)	(0.44)	(1.50)	(1.06)
49 Ind	-0.395	-2.082	-0.603	0.418	-1.934	1.712	-2.309	-1.376	-1.012
	(-0.47)	(-1.52)	(-0.64)	(0.42)	(-1.48)	(1.42)	(-1.27)	(-1.03)	(-0.92)
10 Mom	-0.467	-0.569	-0.309	0.491	-0.435	2.080	-0.323	-0.738	-0.946
	(-0.41)	(-0.50)	(-0.46)	(0.42)	(-0.41)	(1.04)	(-0.20)	(-0.74)	(-0.77)

Table 3.11: Portfolio sorts on the innovations of the estimated state variables

Entries report the monthly post-ranking performance of decile stock portfolios constructed on the basis of their one-month beta estimates on the innovations of the first two principal components (columns PC1 and PC2), the two variables extracted from the Reduced-Rank Regressions described in Section 3.2 (columns RR1 and RR2), the Three-Pass Regression Filter procedure described in Section 3.3 (column 3PRF), or the single one-, three-, six-, and twelve-month horizon (columns 1, 2, 3, 6, and 12-month) of the 2nd (Panel A), the 3rd (Panel B), and the 4th (Panel C) Risk-Neutral Cumulant of the S&P 500 return distribution, separately. At the end of each rolling one-month period, we run the following regression on the daily returns of each stock during the previous three months

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{\Delta SV}^i \Delta SV_t + \varepsilon_{i,t},$$

where ΔSV is the innovation of one of the variables described above. Then, we sort stocks in ascending order with respect to their $\beta_{\Delta SV}^i$ estimate and assign them to ten equally populated portfolios. We form value-weighted portfolio by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) in the portfolio at the end of the beta estimation period. For each portfolio, we record its value-weighted subsequent monthly return (post-ranking returns). The table reports the Fama-French-Carhart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD for the portfolio containing the stocks with the lowest (highest) $\beta_{\Delta SV}^i$ in row Decile-1 (Decile-10) and the spread portfolio in row (10) – (1). t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

	Fama-French Carchart 4 factor alpha (α_{FFC})								
	PC1	PC2	RR1	RR2	3PRF	1M	3M	6M	12M
Panel A: 2nd Risk-Neutral Cumulant									
Decile - 1 α_{FFC}	0.03	-0.61**	-0.47*	-0.65**	-0.55**	-0.16	-0.06	-0.35	-0.11
	(0.13)	(-2.74)	(-1.82)	(-2.61)	(-2.49)	(-0.69)	(-0.23)	(-1.61)	(-0.50)
Decile - 10 α_{FFC}	-0.05	-0.56**	-0.13	-0.48	-0.53**	-0.08	-0.08	-0.21	-0.42*
	(-0.24)	(-2.46)	(-0.50)	(-1.63)	(-2.40)	(-0.40)	(-0.33)	(-0.87)	(-1.88)
(10 – 1) α_{FFC}	-0.08	0.05	0.33	0.17	0.02	0.08	-0.02	0.14	-0.31
	(-0.23)	(0.14)	(0.82)	(0.41)	-1.49	(0.24)	(-0.04)	(0.41)	(-0.95)
Panel B: 3rd Risk-Neutral Cumulant									
Decile - 1 α_{FFC}	-0.18	-0.32*	-0.16	-0.40	-0.64**	-0.32	-0.19	-0.10	-0.58**
	(-0.71)	(-1.83)	(-0.60)	(-1.34)	(-2.84)	(-1.34)	(-0.83)	(-0.38)	(-2.42)
Decile - 10 α_{FFC}	-0.41*	-0.68***	-0.30	-0.38	-0.31*	-0.47**	-0.23	-0.48**	-0.84***
	(-1.80)	(-3.02)	(-1.21)	(-1.39)	(-1.82)	(-2.14)	(-1.03)	(-2.01)	(-3.75)
(10 – 1) α_{FFC}	-0.23	-0.36	-0.14	0.02	0.33	-0.15	-0.03	-0.38	-0.27
	(-0.66)	(-1.48)	(-0.42)	(0.07)	(1.34)	(-0.46)	(-0.09)	(-0.98)	(-0.79)
Panel C: 4th Risk-Neutral Cumulant									
Decile - 1 α_{FFC}	-0.32	-0.76***	-0.49**	-0.68**	-0.68**	-0.21	-0.09	-0.43**	-0.55**
	(-1.43)	(-3.23)	(-2.10)	(-2.53)	(-2.86)	(-0.99)	(-0.40)	(-1.99)	(-2.33)
Decile - 10 α_{FFC}	-0.40	-0.07	-0.64**	-0.30	-0.08	-0.44*	-0.42*	-0.25	-0.40*
	(-1.58)	(-0.42)	(-2.36)	(-1.00)	(-0.49)	(-1.69)	(-1.78)	(-1.08)	(-1.69)
(10 – 1) α_{FFC}	-0.08	0.69**	-0.14	0.38	0.60**	-0.23	-0.33	0.19	0.15
	(-0.21)	(2.79)	(-0.49)	(0.87)	(2.33)	(-0.68)	(-0.89)	(0.50)	(0.46)

Table 3.12: Portfolio sorts on Risk-Neutral Skewness (levels and innovations)

Entries report the monthly post-ranking performance of the lowest, highest, and spread portfolio of decile stock portfolios constructed on the basis of the stocks' beta exposure on the level (Panel A) and the innovation (Panel B) of the Risk-Neutral Skewness (RNS) of the S&P 500 return distribution. At the end of each rolling one-month period, we run the following regression on the daily returns of each stock during the previous one (columns 1-month Betas), three (columns 3-months Betas), and six-months (columns 6-month Betas)

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{\Delta SV}^i X_t + \varepsilon_{i,t},$$

where X_t is either the level (RNS_t) or the innovations ($\Delta \mathrm{RNS}_t$) of the RNS with horizon one (subcolumns 1M), three (subcolumns 3M), and six (subcolumns 6M) months. We then sort stocks in ascending order with respect to their β_X^i estimate and assign them to ten equally populated portfolios. We form value-weighted portfolios by weighting each stock in the portfolio by its relative market value (stock price times the number of shares outstanding) in the portfolio at the end of the beta estimation period. For each portfolio we record its value-weighted subsequent monthly return (post-ranking returns). The table reports the value-weighted β_X^i and Fama-French-Carhart four-factor alpha estimated by running a time series regression of the post-ranking value-weighted monthly returns on monthly $R_m - R_f$, SMB, HML, and UMD for the portfolio containing the stocks with the lowest (highest) β_X^i in row Portfolio-1 (Portfolio-10) and the spread portfolio in row (10) – (1). t-values calculated using Newey-West standard errors with 5 lags are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

	1-month Betas			3-month Betas			6-month Betas		
	1M	3M	6M	1M	3M	6M	1M	3M	6M
Panel A: Levels of Risk-Neutral Skewness (*RNS*)									
Decile – 1 beta	-8.69	-12.59	-19.58	-3.52	-4.73	-7.29	-2.06	-2.80	-4.03
α_{FFC}	-0.39*	-0.84***	-0.86***	-0.14	-0.29	-0.51**	-0.06	-0.21	-0.48**
$t(\alpha_{FFC})$	(-1.77)	(-3.70)	(-3.01)	(-0.68)	(-1.20)	(-2.11)	(-0.22)	(-0.76)	(-2.12)
Decile – 10 beta	8.21	11.38	17.40	3.08	3.99	5.90	1.80	2.30	3.01
α_{FFC}	-0.45**	-0.21	-0.18	-0.41*	0.05	-0.44*	-0.18	-0.02	-0.21
$t(\alpha_{FFC})$	(-2.15)	(-1.06)	(-0.85)	(-1.79)	(0.21)	(-1.67)	(-0.64)	(-0.09)	(-0.68)
Spread 10 – 1 beta	16.90	23.97	36.98	6.60	8.73	13.19	3.86	5.10	7.03
α_{FFC}	-0.06	0.63**	0.67*	-0.27	0.34	0.07	-0.12	0.18	0.27
$t(\alpha_{FFC})$	(-0.20)	(2.13)	(1.87)	(-0.82)	(0.96)	(0.19)	(-0.27)	(0.45)	(0.67)
Panel B: Innovations of Risk-Neutral Skewness (*ΔRNS*)									
Decile – 1 beta	-10.16	-15.42	-24.27	-5.29	-7.62	-11.83	-3.58	-5.16	-8.00
α_{FFC}	-0.07	-0.12	-0.49**	-0.02	-0.28	-0.13	-0.32	-0.16	-0.45*
$t(\alpha_{FFC})$	(-0.35)	(-0.51)	(-2.01)	(-0.12)	(-1.14)	(-0.65)	(-1.15)	(-0.66)	(-1.89)
Decile – 10 beta	15.68	11.38	24.91	5.40	7.69	12.47	3.77	5.33	8.60
α_{FFC}	-0.58**	-0.57**	-0.55**	-0.49*	-0.27	-0.43*	-0.22	-0.15	-0.53*
$t(\alpha_{FFC})$	(-2.05)	(-2.47)	(-2.31)	(-1.88)	(-1.24)	(-1.67)	(-0.82)	(-0.64)	(-1.91)
Spread 10 – 1 beta	20.44	31.09	49.18	10.69	15.31	24.29	7.35	10.49	16.59
α_{FFC}	-0.51	-0.45	-0.06	-0.47	0.01	-0.30	0.09	0.00	-0.08
$t(\alpha_{FFC})$	(-1.34)	(-1.26)	(-0.15)	(-1.51)	(0.03)	(-0.78)	(0.22)	(0.01)	(-0.21)

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